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Selecting the Optimal Green Agricultural Products Supplier: A Novel Approach Based on GBWM and PROMETHEE II

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Abstract: Due to the uncertainty of natural factors and a larger global population, the work of supplying sustainable agricultural materials, especially green agricultural products, faces enormous challenges. How to effectively evaluate and select the most desirable green agricultural material supplier is an urgent issue for both agribusiness and government. In this paper, an integrated q-rung orthopair fuzzy (q-ROF) group best–worst method (GBWM) and the PROMETHEE II was introduced to availably solve such issue. Firstly, by taking similarity degree into account to solve incomplete weight information, a novel technique was constructed to determine the experts' weight reasonably under the q-ROF context. Secondly, to improve consistency for group decision making and obtain a highly reliable selection result, the GBWM was used to derive criteria weights. Then, based on the proposed generalized p-norm knowledge-based score function, the PROMETHEE II was further improved to rank the feasible alternatives. After that, a representative case under the background of green agricultural material supplier selection was investigated in depth. Finally, the detailed comparative technique was conducted to verify the validity and superiority of the improved method.

Keywords: green agricultural material supplier selection; q-rung orthopair fuzzy sets; knowledge-based score function; group best-worst method; PROMETHEE II

1. Introduction

With the continuous improvement of people's living standards and quality, more attention has been paid to green and healthy lifestyles, as well as increasing demands for agricultural products. In today's complicated and volatile environmental conditions, sustainable and stable supply of green agricultural products largely depends on a highly efficient supply chain [1]. Among the whole production process, the supplying of primal material is regarded as a crucial and indispensable link in the chain [2]. That is, supplier selection has a significant impact on today's agricultural industry, especially for agribusinesses and even the government.

With the pace of agricultural modernization advances continuing to increase, agricultural supply chain (ASC) holds a dominant position in agricultural socialization services [3]. After the production of primary agricultural products, ASC includes several other core operations: storage, processing, distribution, and consumption, which is presented in Figure 1 [4]. Differing from other existing industries, several unique characteristics of agriculture industry are [2]: (1) In most situations, each participant in the complete ASC system is probably from separated geographical locations all

around the world, encompassing farmers, processors, distributors, and retailers, so the agricultural products purchased by final consumers belong to diverse farms, various areas, and markets. (2) As a kind of product with enormous variety and quantity, it requires high functions of marketing channels; however, because of the contradiction between the regionality of production and the universality of consumption, the distribution channel is more complicated. (3) Restricted and influenced by natural conditions, the output is unstable. Furthermore, a contradiction between supply and demand also exists pervasively. The safety of the agricultural products needs more attention and concern [5]. From the perspective of sustainability, it is a worldwide trend that agricultural enterprises are increasingly actively implementing green public procurement (GPP) [6,7] in order to better achieve economic and environmental benefits. Moreover, the development of green products has practical significance for protecting the ecological environment, improving the quality of agricultural products, promoting the development of food industry, as well as improving people's health [1]. Thus, as for an enterprise, how to pick up the optimal green agricultural product supplier under a highly uncertain decision-making environment is particularly important.

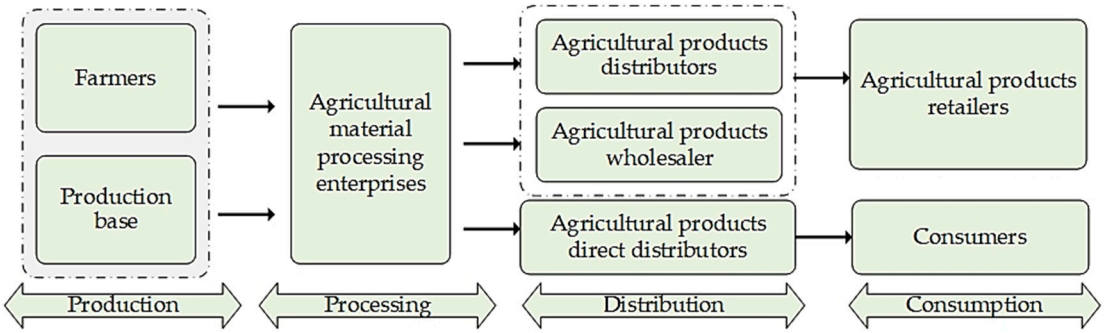

Figure 1. The core operations of agricultural supply chain (ASC) [4].

Regarding the supplier selection, an expert must select the optimal one from several feasible alternatives according to a group of defined criteria, so the issue of green agricultural product supplier selection is identified as a classical multicriteria decision-making (MCDM) problem [8–10]. The most basic and crucial process of handling this issue is collecting the evaluation information provided by experts. However, in most of the practical cases, many factors may impact the decision behaviors of decision makers (DMs), such as the increasingly complicated decision-making environment, uneven levels of expertise, various personalities, as well as subjective judgments, all of which limit the ability of experts to express their actual preference information accurately. That is, this situation may result in the appearance of vagueness and uncertainty for decision-making. Thus, some uncertain techniques, such as fuzzy sets (FSs) [11], intuitionistic FSs (IFSs) [12] and Pythagorean FSs (PFSs) [13], etc., have been introduced to tackle such cases. As is well known, the notion of FSs was originally proposed by Zadeh [11], which can assist DMs in expressing the imprecision in the assessment procedure by means of several crisp numbers. Later, to depict the preference and evaluation information in a more comprehensive and accurate way, the extended form of FSs, namely IFSs and PFSs, have been proposed to deal with complicated decision-making information with fewer restrictions. However, the range of IFSs and PFSs is narrowed by the membership grades. Thus, DMs cannot flexibly depict their true evaluation or preference on the supplier selection.

Recently, by combining the notion of the IFS with the q-rung negation, a novel information form of orthopair fuzzy sets (OFSs) with the name of q-rung OFSs (q-ROFSs) was proposed by Yager [14]. Different from the existing IFSs and PFSs, the space of the MD and NMD of the q-ROFSs is larger and wider, as well as satisfying the restriction that the result summed by q power of the MD and NMD is equal or less than one [15]. We can easily find that as q gets larger, the practicable membership grade range also increases. Moreover, when the values of q are assigned by the number of one or two, respectively, the q-ROFSs degenerate to the ordinary IFSs or PFSs. That is, q-ROFSs is viewed as the generalized form

of diverse existing OFSs. Therefore, as a general and forceful technique, the q-ROFSs have the capability of allowing the experts to depict their actual opinions and assessment information in a more flexible way with larger feasible MD and NMD under complicated decision-making cases. At the same time, many studies have focused on the application of q-ROFSs from various fields and multiple perspectives, including information measure, aggregation operators, decision-making methods, etc. For example, Liu and Wang [16] presented us two aggregation operators, respectively based on averaging operator as well as geometric operator to tackle the q-ROF decision-making. Additionally, Liu et al. [15] provided us a q-ROFSs decision-making method based on another aggregation operator—Heronian mean operator, which can consider the interrelation among different criteria.

Nevertheless, the q-ROFSs have not been studied in green agricultural product supplier selection, which largely limits the expression of DMs. Hence, for green agricultural product supplier selection issues, the q-ROFSs are utilized to depict the evaluation information by DMs, which ensures that the experts are more flexible and have fewer restrictions in describing their true opinions. In addition, in this paper, we found that both the commonly used score function and some improved forms to address q-ROFSs may result in some undesirable results. Then, as a feasible comparison solution to this issue, we propose a novel score function based on the notion of p-norm knowledge-based measure.

As we all know, the MCDM method is widely applied in diverse fields [17]. Up to now, many classical decision-making techniques have studied tackling the supplier selection. For example, the technique of order preference by similarity of ideal solution (TOPSIS) [18], preference ranking organization methods for enrichment evaluation (PROMETHEE) [19], as well as some popular combined methods, such as the VIKOR based on DS theory [20], and the integrated AHP and GRA [21]. In detail, the TOPSIS method [18] considers the distance between each alternative and the positive and the negative ideal points comprehensively. Meanwhile, the PROMETHEE method [19] is simplified and the calculation process is easy to understand.

However, from the extensive literature on classical supplier assessment and selection, only comparatively few studies have focused on the green agricultural industry [22]. Among these decision-making methods, the traditional overall ranking technique PROMETHEE attaches much importance to the evaluation information provided by experts and works on different types of criteria simultaneously, can be qualitative and quantitative, and needs much less inputs. What's more, among the whole PROMETHEE family, the PROMETHEE II [19] has the capability of obtaining the complete ranking concerning several alternatives. Compared with other methods, the outstanding superiority of PROMETHEE II in the process of calculation lies in the simplicity of its comparative technique. Moreover, the PROMETHEE II has not been utilized in selecting green agricultural product supplier under q-ROF environment. By recognizing this, the PROMETHEE II was utilized to rank the feasible suppliers in this paper, then the enterprises could reasonably evaluate and choose the optimal supplier to cooperate.

In the MCDM process, it is indispensable to determine each criterion weight, which also denotes the degree of relative importance. During the past few decades, fruitful efforts have focused on the introduction of deriving the criteria weights by means of different techniques. AHP was originally developed in Saaty [23], which can be viewed as one of the most popular and common methods to determine the criteria weights. The method has the capability to solve subjective judgments and include multiple DMs in the decision-making situation. However, if the preference degree of option A to B cannot be properly depicted, abnormal phenomena will occur in the process of gaining the weights. In addition, among n criteria, normally $n(n-1)/2$ comparisons are required to calculate the final weightings. That is, when the number of criteria increases dramatically, the calculation process will be tedious, as well as time consuming. Recently, aiming at the insufficiency in AHP, Rezaei [24] provided us a novel best–worst method (BWM), which only utilizes $2n-3$ pairwise comparisons and has the capability to greatly improve the consistency of comparisons. The prominent characteristic of BWM is that the best and worst criterion should be identified before the process of comparison, and then we need to determine the preference degree of the most desirable criterion over others, as well

as all other criteria over the least desirable criterion, and finally the weights concerning each criterion can be obtained by means of the model defined in [24]. Due to the simplicity of the method and the dependability of the obtained results, abundant studies have paid attention to utilize the BWM to derive each criterion weights, meanwhile, combining with other existing methods to rank the feasible alternatives or applying in the practical application. In Abadi [25], a BWM framework was presented for medical tourism development in Iran. However, the application of the above-mentioned technique ignores the significance of multiple DMs towards the evaluation results and cannot play the role of group decision making (GDM). Therefore, motivated by Safarzadeh et al. [26], we constructed the group best–worst method (GBWM) under the q-ROF context with the comprehensive model by taking the DMs' weights into account to obtain the reasonable criteria weights for supplier selection.

The motivation of this paper was to deal with the selection of green agricultural product supplier effectively by integrating GBWM method with the PROMETHEE II, which can obtain reasonable rankings of agricultural material suppliers, as well as consider the significance of different experts. Meanwhile, the PROMETHEE II was improved by combining the generalized p-norm knowledge measure of q-ROFS, which provides a comprehensive distance measure of q-ROFSs. Then, the detailed study was further developed by the following aspects:

1. Based on the background of supplier selection in green agricultural industry, the q-ROFSs were utilized to express the assessment values of DMs, for the sake of giving DMs more flexibility and freedom. Meanwhile, aiming at some deficiency of the existing comparison methods of q-ROFSs, the generalized p-norm knowledge-based score function of the q-ROFSs was constructed to reasonably compare any two q-ROFNs and lay a foundation for the application of PROMETHEE II method under the q-ROF context.
2. To deal with incomplete weight information, a novel technique was constructed to derive the experts' weights based on the similarity degree of q-ROFSs, which attaches importance to the distinction among the nonhomogeneous DMs due to their special skills, experience, and even different personalities. Meanwhile, by considering the significance of various experts and GDM, the GBWM was utilized to derive each criterion weights through establishing the q-ROF evaluation matrix, and thus to reasonably obtain the optimal weights.
3. The improved q-ROF PROMETHEE II method is presented by integrating the proposed p-norm knowledge-based score function of q-ROFSs to rank the feasible green agricultural product suppliers, which takes the inherent fuzziness of q-ROFSs into account and depicts the evaluation information denoted by MD and NMD.

In a nutshell, this work aimed at settling the MCDM problems of green agricultural product supplier selection. Specifically, the GBWM technique was utilized to determine the weights of criteria in a scientific and effective way, and the improved PROMETHEE II was used to get the ranking orders. The framework of this paper is depicted as follows. In Section 2, several literature sources are reviewed concerning agricultural industry, such as agricultural supply chain and existing MCDM methods of supplier selection. Then, some basic notions and the generalized p-norm knowledge measures of q-ROFS have been presented and attractive features are also deeply analyzed in Section 3. Furthermore, combined with the GBWM, we improved the PROMETHEE II method by adding the notion of the generalized p-norm knowledge-based score function under the q-ROF environment in Section 4, the calculation steps about the improved method are also given in detail. Finally, in Section 5 we provide an illustrative study case to describe the proposed method in depth and verify the availability and prominent advantages of our method.

2. Literature Review

Supplier selection is a hot issue of common concern for both the academic circles and enterprises nowadays, which can be viewed as a common and classical MCDM problem [27]. The ultimate purpose is to pick the optimal supplier among numerous alternatives, and the reliability of the selected supplier

is influenced by the rest of the supply chain [28]. Over the past few years, the existing literature concerning the problem of supplier selection has been rich in studies, which presents us fruitful individual and comprehensive methods for tackling this issue, as well as systematically summarizing the previous studies in many review papers.

Some scholars have focused on modeling such problems by an individual technique. From the AHP viewpoint, Deng et al. [27] extended the original AHP to D numbers context for the supplier selection by taking negative impact of DMs' subjective judgment on selection results into consideration, which can adequately handle the issue of imprecision and incompleteness. Overall, we obtained from the existing research that the application of AHP under complicated environment in the supplier selection provides the DMs with the confidence of consistency throughout the decision process. From the point view of PROMETHEE, as a traditional ranking technique, various researchers have worked on the PROMETHEE to effectively tackle the supplier selection in diverse fields. For instance, by attaching importance to DMs' personal choice regarding each alternative, the IFS-PROMETHEE was developed by Krishankumar et al. [29]. The framework can be divided into two steps, including utilizing the LBA operator to directly aggregate experts' preference scores, as well as using the PROMETHEE with IFS information to rank the available suppliers. In addition, Esra et al. [30] provided us with a fuzzy PROMETHEE technique to deal with supplier selection, the predefined preference functions of which were handled based on fuzzy distances between feasible alternatives. In addition, TOPSIS method was utilized to select the most satisfied supplier firm under probabilistic linguistic context [18]. All in all, diversiform methods were proposed and applied in dealing with supplier selection with different information [24].

Nevertheless, the above literature almost all utilized the subjective weights of each criterion provided by DMs, that is, the criteria weights were assigned directly. This case may result in the unreasonable and inaccurate ranking results for selecting the most satisfied suppliers. As a solution to this issue, several researchers have worked on the valid calculation process of determining the criteria weights by proposing the integrated methods [31]. A supplier selection framework was constructed for SCM by Wang et al. [21], AHP and GRA were integrated to calculate the criteria weights and further rank the available suppliers respectively. Jain et al. [32] weighed the criteria by means of fuzzy AHP, and then presented a combined technique namely fuzzy AHP and TOPSIS to handle a supplier selection issues in an automobile company.

To mention supplier selection in the agricultural industry, the green agricultural product supplier selection is regarded as a crucial link in the operation process of retailers and also provides one of the great concerns to researchers in academic and applied fields. It is exactly because of the significance of supplier selection of green agricultural products, and to ensure the safety of agricultural products and foods simultaneously, that major production, circulation, and retail enterprises attach importance to the control of the front end of the supply chain [22]. In other words, the increasingly perfected requirements are put forward to the green agricultural product supplier, mainly including the following perspectives [31]: (1) quality safety of green products, (2) performance of suppliers, (3) environmental protection, (4) continuous improvement, and (5) social responsibility. In short, two ultimate goals of green supply chain management are meeting consumers' demands and providing high quality product. To further focus on green agricultural product supplier, a series of laws and policies were carried out by governments and relevant departments, which strengthened laws and regulations in the field of agriculture.

Regarding the distinct characteristics of agricultural products, several MCDM methods have been developed in recent years. In detail, Lu et al. [33] applied TOPSIS method to select optimal agricultural machinery product suppliers under a probabilistic linguistic environment, whereas Cheraghalipour et al. [34] combined BWM with VIKOR to consider supplier selection under the whole framework of the Iranian agricultural industry. Moreover, owing to the commonly encountered multi-attribute issue in the previous study, AHP was further extended to analyze and evaluate agricultural product supplier selection.

For example, Wang et al. [35] utilized the AHP-VIKOR to select the optimal technologies among agricultural industries to tackle agriculture residues.

3. The Generalized p-Norm Knowledge Measure of q-ROFS

3.1. q-ROFSs

In this section, we recall some basic notions and operational rules related to q-ROFSs.

Definition 1 ([14]). *Let $Y = \{y_1, y_2, \ldots, y_n\}$ be a non-empty finite set, the form of q-ROFS $\overline{A}$ in Y can be represented by*

$$\overline{A} = \left\{ < Y, u_{\overline{A}}(y), v_{\overline{A}}(y) > \middle| y \in Y \right\} \tag{1}$$

where $u_{\overline{A}} : Y \to [0,1]$ and $v_{\overline{A}} : Y \to [0,1]$ are the MD and the NMD of $y \in Y$ in $\overline{A}$, respectively, which holds that $0 \le u^q_{\overline{A}}(y) + v^q_{\overline{A}}(y) \le 1$ and $q \ge 1$ for every $y \in Y$. In addition, the hesitancy degree is given in the form of $\pi_{\overline{A}} = \left(1 - u^q_{\overline{A}}(y) - v^q_{\overline{A}}(y)\right)^{\frac{1}{q}}$. For convenience, $\left(u_{\overline{A}}(y), v_{\overline{A}}(y)\right)$ is called a q-ROF number (q-ROFN), simplified as $\left(u_{\overline{A}}, v_{\overline{A}}\right)$.

Definition 2 ([36]). *Let $\gamma = \left(u_\gamma, v_\gamma\right)$ and $\tau = (u_\tau, v_\tau)$ are two $q-$ROFNs and $\lambda > 0$, the operations are as follows:*

$$\gamma \oplus \tau = \left\langle \left(u^q_\gamma + u^q_\tau - u^q_\gamma u^q_\tau\right)^{\frac{1}{q}}, v_\gamma v_\tau \right\rangle \tag{2}$$

$$\gamma \otimes \tau = \left\langle u_\gamma u_\tau, \left(v^q_\gamma + v^q_\tau - v^q_\gamma v^q_\tau\right)^{\frac{1}{q}} \right\rangle \tag{3}$$

$$\lambda\gamma = \left\langle \left(1 - \left(1 - u_\gamma\right)^\lambda\right)^{\frac{1}{q}}, v^\lambda_\gamma \right\rangle \tag{4}$$

$$\gamma^\lambda = \left\langle u^\lambda_\gamma, \left(1 - \left(1 - v^q_\gamma\right)^\lambda\right)^{\frac{1}{q}} \right\rangle. \tag{5}$$

Definition 3 ([37]). *Let any two $q-$ROFSs $\overline{A} = \left\{ < y, u_{\overline{A}}(y), v_{\overline{A}}(y) > \middle| y \in Y \right\}$ and $\overline{B} = \left\{ < y, u_{\overline{B}}(y), v_{\overline{B}}(y) > \middle| y \in Y \right\}$ in a non-empty finite set Y, and $\pi_{\overline{A}}$ denotes the hesitancy degree, the distance measure is*:

$$d_{q-ROF}(\overline{A}, \overline{B}) = \left(\frac{1}{2}\left(\left(u^q_{\overline{A}}(y) - u^q_{\overline{B}}(y)\right)^2 + \left(v^q_{\overline{A}}(y) - v^q_{\overline{B}}(y)\right)^2 + \left(\pi^q_{\overline{A}}(y) - \pi^q_{\overline{B}}(y)\right)^2\right)\right)^{\frac{1}{2}}. \tag{6}$$

3.2. Analysis of the Existing Comparative Methods of q-ROFSs

As is well known, the common comparative methods for any two q-ROFNs are generally based on the defined function [36,38]. To mention it, an unreasonable phenomenon has occurred in the existing comparative methods of q-ROFSs, which may result in some undesirable results. Then, the detailed analysis can be shown as follows.

(a) Liu and Wang's score function [36].

Definition 4 ([36]). *Let $\overline{A} = \left(u_{\overline{A}}, v_{\overline{A}}\right)$ and $\overline{B} = \left(u_{\overline{B}}, v_{\overline{B}}\right)$ are two q-ROFNs, then the score function $S(\overline{A})$ and the accuracy function $H(\overline{A})$ can be expressed as:*

$$S\left(\overline{A}\right) = u^q_{\overline{A}} - v^q_{\overline{A}} \tag{7}$$

$$H\left(\overline{A}\right) = u_{\overline{A}}^{q} + v_{\overline{A}}^{q}. \tag{8}$$

According to Definition 4, the comparative method is depicted as follows: if $S(\overline{A}) \succ S(\overline{B})$, then $\overline{A} \succ \overline{B}$; otherwise, if $S(\overline{A}) = S(\overline{B})$, then the result can depend on the values of accuracy function. In detail, if $H(\overline{A}) \succ H(\overline{B})$, then $\overline{A} \succ \overline{B}$; if $H(\overline{A}) = H(\overline{B})$, then $\overline{A} = \overline{B}$.

Remark 1. *It can easily be observed that the above comparison method may result in unreasonable results, that is, when the value of q changes, the comparison results are completely reversed, which is counterintuitive. In addition, the above comparative method ignores the inherent uncertainties and vagueness of q-ROFSs, as well as the influence of abstention, all these may also lead to the undesirable phenomenon and weaker precision.*

Example 1. *Suppose* $q = 1.5$ *, take* $\overline{A} = (0.6, 0.3)$ *and* $\overline{B} = (0.5, 0.1)$ *for example, based on Equation (7), the obtained score function values are* $S(\overline{A}) = 0.3004$ *and* $S(\overline{B}) = 0.3219$ *, then* $\overline{A} \prec \overline{B}$ *. However, when q is assigned to the value of 3, then the obtained results are* $S(\overline{A}) = 0.1890$ *and* $S(\overline{B}) = 0.1240$ *, respectively, that is,* $\overline{A} \succ \overline{B}$*. Therefore, the comparison method based on Definition 4 is unreasonable.*

(b) Wei et al.'s score function [38].

Definition 5 ([38]). *Let* $\overline{A} = \left(u_{\overline{A}}, v_{\overline{A}}\right)$ *be a q-ROFN, and then the score function and the accuracy function represented in* [38] *can be as:*

$$S\left(\overline{A}\right) = \frac{1}{2}\left(1 + u_{\overline{A}}^{q} - v_{\overline{A}}^{q}\right) \tag{9}$$

$$H\left(\overline{A}\right) = u_{\overline{A}}^{q} + v_{\overline{A}}^{q}. \tag{10}$$

In addition, Wei et al.'s comparative method for any two q-ROFNs is the same as [36].

Remark 2. *Although the above defined score function is different from Liu and Wang's* [36]*, the same problem occurs in this method, that is, with the transformation of the value of q , thecomparison results change.*

(c) Peng et al.'s score function [39].

Definition 6 ([39]). *For a q-ROFN* $\overline{A} = \left(u_{\overline{A}}, v_{\overline{A}}\right)$ *, the score function is:*

$$S\left(\overline{A}\right) = u_{\overline{A}}^{q} - v_{\overline{A}}^{q} + \left(\frac{e^{u_{\overline{A}}^{q} - v_{\overline{A}}^{q}}}{e^{u_{\overline{A}}^{q} - v_{\overline{A}}^{q}} + 1} - \frac{1}{2}\right)\pi^{q}. \tag{11}$$

Remark 3. *It is shown that the improved score function described in Equation (11) provides unreasonable results in cases of* $u_{\overline{A}} = v_{\overline{A}}$ *. Regardless, whatever the value of q is, it always gives value 0.*

Example 2. *Suppose* $\overline{A} = (0.6, 0.6)$ *and* $\overline{B} = (0.3, 0.3)$ *, if we utilize the Peng et al. 's score function to select the optimal one, then the score function* $S\left(\overline{A}\right) = 0$ *, as well as* $S\left(\overline{B}\right) = 0$ *. That is, this method cannot distinguish the distinction of* $\overline{A}$ *and* $\overline{B}$ *in this case, hence, it lacks the ability of obtaining the order of q-ROFNs with the condition* $u_{\overline{A}} = v_{\overline{A}}$*.*

3.3. The Generalized p-Norm Knowledge-Based Score Function of q-ROFSs

To solve similar unreasonable comparison result, inspired by Nguyen's method [40], we present a notion of knowledge measure for q-ROFs to compare any two q-ROFSs, which have the characteristic

of portraying information conveyed by the MD and NMD, as well as considering the inherent fuzziness of q-ROFSs.

Definition 7. *Let Y be a finite universal set, a q-ROFN $\overline{A}$ is defined by the form of $\left\langle u_{\overline{A}}(y), v_{\overline{A}}(y)\right\rangle$. The generalized knowledge measure of $\overline{A}$ is consist of a normalized sum of its p-norm distance from the reference q-ROFS $Q = \langle y, 0, 0\rangle$ and p-norm variation between its MD and NMD. The normalized p-norm distance from the reference $Q = \langle y, 0, 0\rangle$ can be denoted by $\left(\left(u_{\overline{A}}^{q}(y) - 0\right)^{p} + \left(v_{\overline{A}}^{q}(y)^{q} - 0\right)^{p} + \left(1 - \pi_{\overline{A}}^{q}(y)\right)^{p}\right)^{\frac{1}{p}}$, and the p-norm variation between its MD and NMD can be expressed as $\left|\left(u_{\overline{A}}^{q}(y)\right)^{p} - \left(v_{\overline{A}}^{q}(y)\right)^{p}\right|^{\frac{1}{p}}$. Then, the generalized p-norm knowledge measure of $\overline{A}$ is listed as follows* $(p = 1, 2, \ldots, n)$:

$$K_F\left(\overline{A}\right) = \frac{1}{2^{\frac{1}{p}} + 1}\left[\left(\left(u_{\overline{A}}^{q}(y)\right)^{p} + \left(v_{\overline{A}}^{q}(y)\right)^{p} + \left(u_{\overline{A}}^{q}(y) + v_{\overline{A}}^{q}(y)\right)^{p}\right)^{\frac{1}{p}} + \left|\left(u_{\overline{A}}^{q}(y)\right)^{p} - \left(v_{\overline{A}}^{q}(y)\right)^{p}\right|^{\frac{1}{p}}\right]. \tag{12}$$

Based on the Definition 7, $K_F(\overline{A})$ meets the following properties:

Theorem 1 (Monotonicity). *Let Y be a finite universal set, a q-ROFN $\overline{A}$ is defined by the form of $\left\langle u_{\overline{A}}(y), v_{\overline{A}}(y)\right\rangle$. Then, the et al.easure $K_F(\overline{A})$ is a monotone function.*

Proof.

(1) Firstly, that $K_F(\overline{A})$ is strictly monotonic with respect to the $u_{\overline{A}}$ is proven by:

$$\frac{\partial K_F\left(\overline{A}\right)}{\partial u_{\overline{A}}} = \frac{\frac{1}{p}}{2^{\frac{1}{p}} + 1}\left[\left(\left(u_{\overline{A}}^{q}\right)^{p} + \left(v_{\overline{A}}^{q}\right)^{p} + \left(u_{\overline{A}}^{q} + v_{\overline{A}}^{q}\right)^{p}\right)^{\frac{1}{p}-1} pq\left(\left(u_{\overline{A}}\right)^{pq-1} + \left(u_{\overline{A}}^{q} + v_{\overline{A}}^{q}\right)^{p-1}\left(u_{\overline{A}}\right)^{q-1}\right)\right.$$

$$\left. + \left|\left(u_{\overline{A}}^{q}\right)^{p} - \left(v_{\overline{A}}^{q}\right)^{p}\right|^{\frac{1}{p}-1} pq\left(u_{\overline{A}}\right)^{pq-1}\right] > 0.$$

(2) Then, we prove $K_F(\overline{A})$ is strictly monotonic with respect to the $v_{\overline{A}}$ by:

$$\frac{\partial K_F\left(\overline{A}\right)}{\partial v_{\overline{A}}} = \frac{\frac{1}{p}}{2^{\frac{1}{p}} + 1}\left[\left(\left(v_{\overline{A}}^{q}\right)^{p} + \left(u_{\overline{A}}^{q}\right)^{p} + \left(u_{\overline{A}}^{q} + v_{\overline{A}}^{q}\right)^{p}\right)^{\frac{1}{p}-1} pq\left(\left(v_{\overline{A}}\right)^{pq-1} + \left(u_{\overline{A}}^{q} + v_{\overline{A}}^{q}\right)^{p-1}\left(v_{\overline{A}}\right)^{q-1}\right)\right.$$

$$\left. + \left|\left(u_{\overline{A}}^{q}\right)^{p} - \left(v_{\overline{A}}^{q}\right)^{p}\right|^{\frac{1}{p}-1} pq\left(v_{\overline{A}}\right)^{pq-1}\right] > 0$$

Therefore, the proof is finished. That is, over the domain space, $K_F(\overline{A})$ is strictly monotonic increasing with the increasing of $u_{\overline{A}}(y)$, $u_{\overline{A}}(y)$. □

Theorem 2. *For $\forall y \in Y$, suppose q-ROFN $\overline{A} = \left\langle u_{\overline{A}}(y), v_{\overline{A}}(y)\right\rangle$ and $\overline{B} = \left\langle u_{\overline{B}}(y), v_{\overline{B}}(y)\right\rangle$, several properties can be derived as follows:*

(1). if $u_{\overline{A}}(y) = v_{\overline{A}}(y) = 0$, then $K_F(\overline{A}) = 0$.
(2). if $u_{\overline{A}}(y) = 1, v_{\overline{A}}(y) = 0$ or $u_{\overline{A}}(y) = 0, v_{\overline{A}}(y) = 1$, then $K_F(\overline{A}) = 1$.
(3). if $u_{\overline{A}}(y) \geq u_{\overline{B}}(y)$ and $v_{\overline{A}}(y) \leq v_{\overline{B}}(y)$, then $K_F(\overline{A}) \geq K_F(\overline{B})$.
(4). $K_F(\overline{A}) = K_F(\overline{A}^{C})$, where $\overline{A}^{C}$ is a complement of $\overline{A}$.

Proof of Theorem 2 (2): Suppose $p = 2, q = 3$, when $u_{\overline{A}}(y) = 1, v_{\overline{A}}(y) = 0$, then

$$K_F\left(\overline{A}\right) = \frac{1}{2^{\frac{1}{p}}+1}\left[\left(\left(u_{\overline{A}}^{q}(y)\right)^{p} + \left(v_{\overline{A}}^{q}(y)\right)^{p} + \left(u_{\overline{A}}^{q}(y) + v_{\overline{A}}^{q}(y)\right)^{p}\right)^{\frac{1}{p}} + \left|\left(u_{\overline{A}}^{q}(y)\right)^{p} - \left(v_{\overline{A}}^{q}(y)\right)^{p}\right|^{\frac{1}{p}}\right]$$

$$= \frac{1}{2^{\frac{1}{2}}+1}\left[\left(1^2+0+1^2\right)^{\frac{1}{2}} + \left|1^2-0\right|^{\frac{1}{2}}\right] = 1.$$

Similarly, when $u_{\overline{A}}(y) = 0, v_{\overline{A}}(y) = 1$, then $K_F(\overline{A}) = 1$.

The rest of properties can be easily proven, so are omitted here. Based on the above analysis, the novel score function of a q-ROFN is defined in the following. □

Definition 8. *Suppose $\overline{A} \in q-ROFS$ be a q-ROFN in a finite universal set $Y = \{y_1, y_2, \ldots, y_n\}$, for $C \gg 0$ and $0 < \delta \ll 1$, then the generalized p-norm knowledge-based score function of $\overline{A}$ is depicted as:*

$$Sco_F(\overline{A}) = \begin{cases} \left[\frac{e^{C(u_{\overline{A}}^{q}(y) - v_{\overline{A}}^{q}(y))} - 1}{e^{C(u_{\overline{A}}^{q}(y) - v_{\overline{A}}^{q}(y))} + 1}\right] K_F(\overline{A}), & if\ u_{\overline{A}}(y) \neq v_{\overline{A}}(y) \\ \delta K_F(\overline{A}), & if u_{\overline{A}}(y) = v_{\overline{A}}(y) \end{cases} \tag{13}$$

in which the coefficient C is regarded as the sigmoidal shape of the defined score function around the points of $u_{\overline{A}} = v_{\overline{A}}$. It is worth highlighting that one superiority and prominent advantage of the knowledge-based score function is attaching importance to the significance of the given evaluation information, whether positive or negative. That is, the final rankings concerning the q-ROFNs are based on the importance of their performance.

Remark 4. *It is worth stressing that for $C \gg 0$, the wiggly range of $Sco_F\left(\overline{A}\right)$ belongs to $[-1, 1]$. In detail, $\forall y \in Y$, when $u_{\overline{A}} > v_{\overline{A}}$, it represents the generalized p-norm knowledge-based score function of a q-ROFN $Sco_F\left(\overline{A}\right) > 0$, the positive assessment is larger than the passive namely. Otherwise, $Sco_F\left(\overline{A}\right) < 0$ represents the NMD is larger than the MD. To mention the special cases of q-ROFNs with $u_{\overline{A}} = v_{\overline{A}}$, it means the positive information is equal to the passive one, that $Sco_F\left(\overline{A}\right) \approx 0$.*

Then, to illustrate the superiority of the proposed score function for comparing two q-ROFNs, the above Examples 1 and 2 will be resolved by means of the comparison method defined in Definition 8.

Example 3. *When $q = 1.5$, similarly, let $\overline{A} = (0.6, 0.3)$ and $\overline{B} = (0.5, 0.1)$, based on Equations (9) and (10), the obtained score function values are $Sco_F(\overline{A}) = 0.5111$ and $Sco_F(\overline{B}) = 0.3628$, then $\overline{A} \succ \overline{B}$. Then, when q is assigned to the value of 3, the obtained results are $Sco_F(\overline{A}) = 0.2239$ and $Sco_F(\overline{B}) = 0.1253$, respectively, then $\overline{A} \succ \overline{B}$. Hence, in our method, when the value of q changes, the compared results are invariable. Obviously, from this perspective, the comparison method based on the generalized p-norm knowledge-based score function better than the method based on the original score function.*

Example 4. *When $\overline{A} = (0.6, 0.6)$ and $\overline{B} = (0.3, 0.3)$, we can calculate the score function based on the Equation (13) that $S\left(\overline{A}\right) = 0.0022$ and $S\left(\overline{B}\right) = 0.0003$ $(q = 3, p = 2, \delta = 0.01)$. Then, the proposed comparative method can tackle the cases when $u_{\overline{A}} = v_{\overline{A}}$.*

The above examples and analysis show the outstanding superiority of the proposed generalized p-norm knowledge-based score function over the existing comparative methods of q-ROFSs. It is shown that the proposed method is free of weakness presented in the existing score function, as well as considering the inherent fuzziness of q-ROFSs and the influence of the hesitancy degree, meaning we can gain more desirable results.

4. An Integrated GBWM-PROMETHEE II Framework for Group Decision Making

In this section, to better tackle the supplier selection in the agricultural industry, based on the proposed generalized p-norm knowledge-based score function and the GBWM method, we improved the traditional PROMETHEE II method under the q-ROF context. In addition, we further discuss the following detailed points for effective evaluation and selection of the optimal agricultural material supplier: (1) The DMs' weights concerning each criterion are determined rather than given directly. (2) The criteria weights are calculated using GBWM method. (3) Combining the GBWM with the improved PROMETHEE II. The main steps of an integrated GBWM-PROMETHEE II framework for GDM are portrayed in Figure 2.

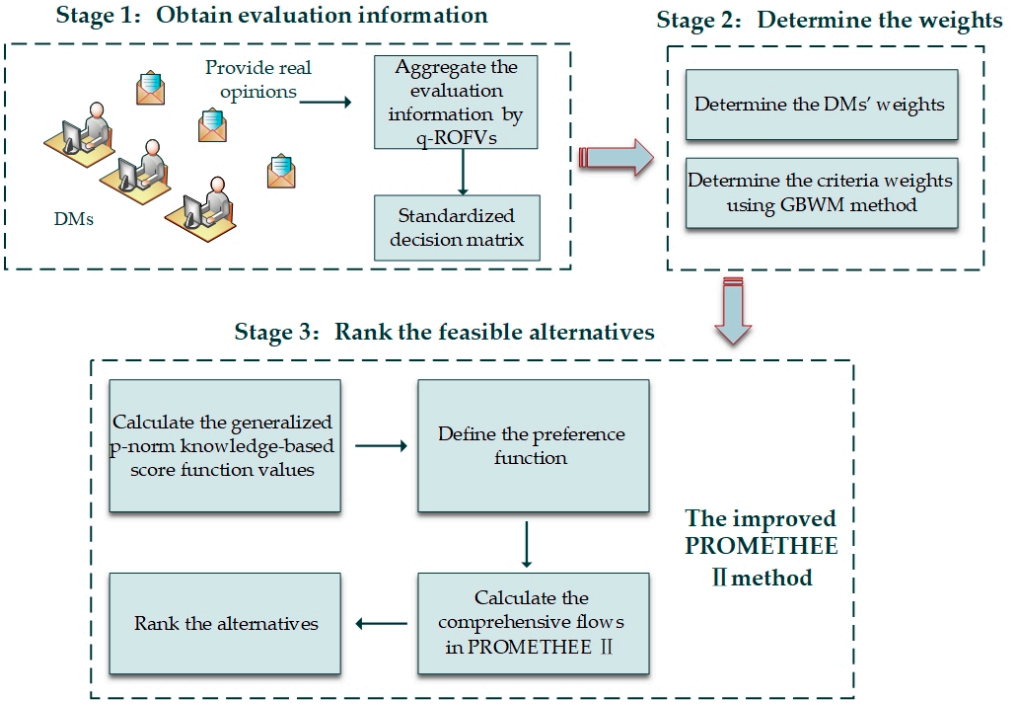

Figure 2. An integrated GBWM-PROMETHEE II framework for group decision making (GDM).

Firstly, the original decision matrix is depicted in Table 1. It is a matrix where $e_\tau(\alpha_\varsigma)$ denotes the performance with respect to the feasible alternative $\alpha_\varsigma(\varsigma = 1, 2, \ldots, m)$ and the corresponding evaluation criterion $e_\tau(\tau = 1, 2, \ldots, n)$. In addition, suppose that ω_τ indicates the weight of each criterion.

Table 1. Original decision matrix.

$\boldsymbol{\alpha}$	$\boldsymbol{e_1(\cdot)}$	$\boldsymbol{e_2(\cdot)}$	$\cdots$	$\boldsymbol{e_\tau(\cdot)}$	$\cdots$	$\boldsymbol{e_n(\cdot)}$
α_1	$e_1(\alpha_1)$	$e_2(\alpha_1)$	$\cdots$	$e_\tau(\alpha_1)$	$\cdots$	$e_n(\alpha_1)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
α_ς	$e_1(\alpha_\varsigma)$	$e_2(\alpha_\varsigma)$	$\cdots$	$e_\tau(\alpha_\varsigma)$	$\cdots$	$e_n(\alpha_\varsigma)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
α_m	$e_1(\alpha_m)$	$e_2(\alpha_m)$	$\cdots$	$e_\tau(\alpha_m)$	$\cdots$	$e_n(\alpha_m)$

4.1. Determine DMs' Weights

In this section, for deriving reasonable DMs' weights instead of assigning the same proportion to all DMs, an innovative method for solving incomplete weight information for MAGDM is introduced. Inspired by Ju [41], we constructed a technique to determine the experts' weights based on the similarity degree of q-ROFSs, which has the capability of characterizing DMs' true feelings in larger practicable membership grades.

The q-ROF decision matrix with the criteria C_τ can be depicted as:

$$X^{(\tau)} = \begin{array}{c} \\ DM_1 \\ DM_2 \\ \vdots \\ DM_\eta \end{array} \begin{array}{c} \begin{array}{cccc} \alpha_1 & \alpha_2 & \cdots & \alpha_m \end{array} \\ \begin{bmatrix} \left(\mu_{11}^\tau, v_{11}^\tau\right) & \left(\mu_{12}^\tau, v_{12}^\tau\right) & \cdots & \left(\mu_{1m}^\tau, v_{1m}^\tau\right) \\ \left(\mu_{21}^\tau, v_{21}^\tau\right) & \left(\mu_{22}^\tau, v_{22}^\tau\right) & \cdots & \left(\mu_{2m}^\tau, v_{2m}^\tau\right) \\ \vdots & \vdots & \cdots & \vdots \\ \left(\mu_{\eta 1}^\tau, v_{\eta 1}^\tau\right) & \left(\mu_{\eta 2}^\tau, v_{\eta 2}^\tau\right) & \cdots & \left(\mu_{\eta m}^\tau, v_{\eta m}^\tau\right) \end{bmatrix} \end{array},$$

where $G = \left\{DM_1, DM_2, \ldots, DM_\eta\right\}$ with $\eta \geq 2$. Assume that $\left(\mu_{\kappa\varsigma}^\tau, v_{\kappa\varsigma}^\tau\right)$ is the evaluation information in the form of q-ROFN given by the κth DM concerning the relative alternatives $\alpha_\varsigma (\varsigma = 1, 2, \ldots, m)$.

Step 1: Determine the mean evaluation value $(\overline{\mu}^\tau{}_\varsigma, \overline{v}^\tau{}_\varsigma)$ for α_ς concerning the criteria C_τ by all DMs.

$$(\overline{\mu}^\tau{}_\varsigma, \overline{v}^\tau{}_\varsigma) = \frac{\sum_{k=1}^{\eta} \left(\mu_{k\varsigma}^\tau, \nu_{k\varsigma}^\tau\right)}{\eta}, \varsigma = 1, 2, \ldots, m; \tau = 1, 2, \ldots, n. \tag{14}$$

Step 2: Based on Equation (6), define the similarity degree between any assessment value $(\mu^\tau{}_{\kappa\varsigma}, v^\tau{}_{\kappa\varsigma})$ and the mean value $\left(\overline{\mu}_\varsigma^\tau, \overline{v}_\varsigma^\tau\right)$ determined by Equation (14):

$$z_{\kappa\varsigma}^\tau = 1 - d_{q-ROF}\left(\left(\left(\mu_{\kappa\varsigma}^\tau, v_{\kappa\varsigma}^\tau\right)\right), \left((\overline{\mu}^\tau{}_\varsigma, \overline{v}^\tau{}_\varsigma)\right)\right). \tag{15}$$

Step 3: Calculate the overall similarity degree of each DM concerning the criteria C_τ by Equation (16):

$$\delta_\kappa^\tau = \sum_{\varsigma=1}^{m} z_{\kappa\varsigma}^\tau. \tag{16}$$

Step 4: Define the weight of each DM as:

$$\omega_\kappa^\tau = \frac{\delta_\kappa^\tau}{\sum_{k=1}^{\eta} \delta_\kappa^\tau}. \tag{17}$$

We can easily determine that Equation (17) satisfies the conditions $\omega_\kappa^\tau \in [0, 1]$ and $\sum_{k=1}^{\eta} \omega_\kappa^\tau = 1$. By adding the notion of similarity degree to the process of analysis, the superiority and prominent advantage of this method is that it attaches importance to the distinction among the nonhomogeneous DMs in their knowledge, experience, skills, and even personality, and thus the decision results we can gain are more reasonable. In the following, the GBWM method is utilized to derive the criteria weights.

4.2. Determining the Criteria Weights Using GBWM Method

By inspiring the characteristics of the BWM, a novel method named the group best–worst method is proposed to derive the criteria weights with GDM problems. Compared with the original BWM method [24], Soroush et al. [26] paid attention to the significance of the DMs for calculating the optimal weights with respect to each criterion.

In this section, we suppose that η experts with respect to n criteria, then the calculation process can be represented as follows:

Step 1: Determine a collection of criteria $C_\tau (\tau = 1, 2, \ldots, n)$ for decision making.

Step 2: Identify the best criterion C_B and the worst criterion C_W, respectively.

In this step, we assume that one specific expert determines C_B and C_W. For GDM, C_B denotes the most desirable criterion and C_W is the least desirable criterion.

Step 3: Utilize the numbers between 1 to 9 to determine the preference of C_B over all the other criteria, simplified as best-to-others (BTO) vector:

$$\overline{A}_B = (\overline{\alpha}_{B1}, \overline{\alpha}_{B2}, \ldots, \overline{\alpha}_{Bn}) \tag{18}$$

where $\overline{\alpha}_{B\tau}$ denotes the preference degree of C_B over C_τ. Note that $\overline{\alpha}_{BB} = 1$.

Step 4: Utilize the numbers between 1 to 9 to determine the preference of all the criteria over C_W, simplified as others-to-worst (OTW) vector:

$$\overline{A}_W = (\overline{\alpha}_{1W}, \overline{\alpha}_{2W}, \ldots, \overline{\alpha}_{nW})^T \tag{19}$$

where $\overline{\alpha}_{\tau W}$ denotes the preference degree of C_τ over C_W. Note that $\overline{\alpha}_{WW} = 1$.

Step 5: Obtain the optimal weights $\omega^* = \left(\omega_1^*, \omega_2^*, \ldots, \omega_n^*\right)$ utilizing M1 in [21] as follows:

$$\text{Min} \sum_{k=1}^{\eta} \varpi_k \text{Max}_{\tau} \left\{ \left| \frac{\omega_B}{\omega_\tau} - \alpha_{B\tau}^k \right|, \left| \frac{\omega_\tau}{\omega_W} - \alpha_{\tau W}^k \right| \right\} St. \sum_{\tau=1}^{n} \omega_\tau = 1 \tag{20}$$

$\omega_\tau \geq 0$, for all τ.

Further, to simplify the model, $\varepsilon_k = \text{Max}_\tau \left\{ \left| \frac{\omega_B}{\omega_\tau} - \alpha_{B\tau}^k \right|, \left| \frac{\omega_\tau}{\omega_W} - \alpha_{\tau W}^k \right| \right\}$ $(k = 1, 2, \ldots, n)$ is defined. Then, the converted model can be represented as:

$$\begin{array}{ll} & \text{Min} \sum_{k=1}^{\eta} \varpi_k \varepsilon_k \\ & St. \\ \left| \frac{\omega_B}{\omega_\tau} - \alpha_{B\tau}^k \right| \leq \varepsilon_k & \tau = 1, 2, \ldots, n, \; k = 1, 2, \ldots, \eta \\ \left| \frac{\omega_\tau}{\omega_W} - \alpha_{\tau W}^k \right| \leq \varepsilon_k & \tau = 1, 2, \ldots, n, \; k = 1, 2, \ldots, \eta \\ & \sum_{\tau=1}^{n} \omega_\tau = 1 \end{array} \tag{21}$$

$\omega_\tau \geq 0$, for all τ.

Solving the above problem (21), then we can gain the optimal weights $\omega^* = (\omega_1{}^*, \omega_2{}^*, \ldots, \omega_n{}^*)$ and ε_k. In addition, the notion of consistency ratio also can be calculated, the value closer to 0 is desired [26].

4.3. Ranking by the Improved PROMETHEE II Method

In this section, for obtaining more reasonable results, we improve the original PROMETHEE II [19] method to rank the feasible alternatives. The dominating processes are introduced as follows:

Step 1: Normalize the original assessment decision matrix $X = [\chi_{\varsigma\tau}]_{m\times n}$ to $\widetilde{X} = [\widetilde{\chi}_{\varsigma\tau}]_{m\times n}$, the method is presented in detail as:

(1) For benefit-type inputs $C_\tau (\tau = 1, 2, \ldots, n)$, then

$$\widetilde{\chi}_{\varsigma\tau} = \chi_{\varsigma\tau} = \langle (\mu_{\varsigma\tau}, \nu_{\varsigma\tau}) \rangle. \tag{22}$$

(2) For cost-type inputs $C_\tau (\tau = 1, 2, \ldots, n)$, then

$$\widetilde{\chi}_{\varsigma\tau} = \langle (\nu_{\varsigma\tau}, \mu_{\varsigma\tau}) \rangle. \tag{23}$$

Step 2: Calculate the deviations $d_\tau (\tau = 1, 2, \ldots, n)$ based on pairwise comparisons and the generalized p-norm knowledge-based score function in Equation (13):

$$d_\tau (\alpha_a, \alpha_b) = Sco_F(\alpha_a) - Sco_F(\alpha_b) \tag{24}$$

where $d_\tau(\alpha_a, \alpha_b)$ indicates the difference between the performance of the feasible alternatives α_a and α_b concerning each criterion.

Step 3: Define the preference function $p_\tau(\alpha_a, \alpha_b)$:

$$p_\tau(\alpha_a, \alpha_b) = F_\tau[d_\tau(\alpha_a, \alpha_b)] \tag{25}$$

where $p_\tau(\alpha_a, \alpha_b)$ indicates the preference of α_a over α_b concerning each criterion, expressed as the function of $d_\tau(\alpha_a, \alpha_b)$. Here, to match the characteristics of the criteria better, one predefined shape of the preference function named the usual (type I) [19] is applied.

That is, $p_\tau(\alpha_a, \alpha_b) = d_\tau(\alpha_a, \alpha_b) = Sco_F(\alpha_a) - Sco_F(\alpha_b)$.

Step 4: Determine the global preference index $\Pi(\alpha_a, \alpha_b)$ by Equation (26):

$$\Pi(\alpha_a, \alpha_b) = \sum_{\tau=1}^{n} p_\tau(\alpha_a, \alpha_b)\omega_\tau \tag{26}$$

where $\Pi(\alpha_a, \alpha_b)$ measures how much α_a over α_b in view of the overall criteria, and the associated weights ω_τ are determined by utilizing the GBWM method in Section 4.2.

Step 5: Aggregate $\Pi(\alpha_a, \alpha_b)$ into the positive $\varphi^+(\alpha_a)$ and negative $\varphi^-(\alpha_a)$ outranking flows by the following equations:

$$\varphi^+(\alpha_a) = \frac{1}{m-1} \sum_{\alpha_b \in A} \Pi(\alpha_a, \alpha_b) \tag{27}$$

$$\varphi^-(\alpha_a) = \frac{1}{m-1} \sum_{\alpha_b \in A} \Pi(\alpha_b, \alpha_a) \tag{28}$$

where $\varphi^+(\alpha_a)$ and $\varphi^-(\alpha_a)$ depict that the preference degree of α_a outranks all other alternatives and is outranked by them, respectively. They can also be regarded as the superiority and weakness of α_a. Note that the larger $\varphi^+(\alpha_a)$ and the smaller $\varphi^-(\alpha_a)$, the better the evaluation information of α_a.

Step 6: Rank the alternatives by calculating the comprehensive net flow $\varphi(\alpha_a)$:

$$\varphi(\alpha_a) = \varphi^+(\alpha_a) - \varphi^-(\alpha_a) \tag{29}$$

Obviously, the higher the net flow, more desirable the alternative we gain.

5. Case Study and Analysis

5.1. Background

The Qingdao Bohai agriculture development corporation is a subsidiary of Shandong Bohai industry group, which is a grain and oil processing enterprise integrating grain and oil processing, international trade, warehousing, and logistics. Taking "Serving the Three Rural Areas and Benefiting the Society" as mission, the corporation continues to pool global industrial superior resources, and is growing gradually in the process of agricultural industrialization. Furthermore, its deep processing fields include soybeans, rapeseed, cereals, oils, and vegetable fibers. For the sake of deep processing high quality soybean better, the management board wants to select a high-grade soybean supplier.

Four soybean suppliers $\{\alpha_1, \alpha_2, \alpha_3, \alpha_4\}$ with the ability to meet the corporation's requirements are entitled to this selection. The evaluation criteria are the most representative summarized from the existing literature on green supplier selection, as well as combining with the company's situation in the reality. Then, the selected six criteria are determined as follows [42,43]: price of green agricultural product (C_1); quality of green agricultural product (C_2), production capacity and technology (C_3), delivery (C_4), environmental management (C_5), and design for environment (C_6).

5.2. The Detailed DM Steps

5.2.1. Determine DMs' Weights

For solving the above-mentioned case, the evaluation information matrix in the form of q-ROFV provided by the three DMs is depicted as Tables A1–A6 ($q = 3$), which is shown in Appendix A.

Step 1: Determine the mean evaluation value $\left(\overline{\mu}_{\varsigma}^{\tau}, \overline{v}_{\varsigma}^{\tau}\right)$ based on Equation (14).

$$\begin{array}{l}
\left(\overline{\mu}_1^1, \overline{v}_1^1\right) = (0.6098, 0.4762); \left(\overline{\mu}_2^1, \overline{v}_2^1\right) = (0.7239, 0.2884); \left(\overline{\mu}_3^1, \overline{v}_3^1\right) = (0.5999, 0.4160); \left(\overline{\mu}_4^1, \overline{v}_4^1\right) = (0.7478, 0.3420); \\
\left(\overline{\mu}_1^2, \overline{v}_1^2\right) = (0.7239, 0.5429); \left(\overline{\mu}_2^2, \overline{v}_2^2\right) = (0.7679, 0.3634); \left(\overline{\mu}_3^2, \overline{v}_3^2\right) = (0.7779, 0.4718); \left(\overline{\mu}_4^2, \overline{v}_4^2\right) = (0.6994, 0.2884); \\
\left(\overline{\mu}_1^3, \overline{v}_1^3\right) = (0.7573, 0.5192); \left(\overline{\mu}_2^3, \overline{v}_2^3\right) = (0.5273, 0.4718); \left(\overline{\mu}_3^3, \overline{v}_3^3\right) = (0.5480, 0.3107); \left(\overline{\mu}_4^3, \overline{v}_4^3\right) = (0.5480, 0.6868); \\
\left(\overline{\mu}_1^4, \overline{v}_1^4\right) = (0.6935, 0.3107); \left(\overline{\mu}_2^4, \overline{v}_2^4\right) = (0.7420, 0.6350); \left(\overline{\mu}_3^4, \overline{v}_3^4\right) = (0.8240, 0.3037); \left(\overline{\mu}_4^4, \overline{v}_4^4\right) = (0.7075, 0.5451); \\
\left(\overline{\mu}_1^5, \overline{v}_1^5\right) = (0.6966, 0.3780); \left(\overline{\mu}_2^5, \overline{v}_2^5\right) = (0.7204, 0.3634); \left(\overline{\mu}_3^5, \overline{v}_3^5\right) = (0.7645, 0.4121); \left(\overline{\mu}_4^5, \overline{v}_4^5\right) = (0.6877, 0.4380); \\
\left(\overline{\mu}_1^6, \overline{v}_1^6\right) = (0.5999, 0.6316); \left(\overline{\mu}_2^6, \overline{v}_2^6\right) = (0.8092, 0.3107); \left(\overline{\mu}_3^6, \overline{v}_3^6\right) = (0.6966, 0.2520); \left(\overline{\mu}_4^6, \overline{v}_4^6\right) = (0.6966, 0.5646).
\end{array}$$

Step 2: Based on Equation (6) and Equation (14), the similarity degrees $z_{\kappa\varsigma}^{\tau}$ ($k = 1, 2, 3$ and $\varsigma = 1, 2, 3, 4$) are depicted in Tables A7–A12, which are shown in Appendix B.

Step 3: Calculate the overall similarity degree of each DM concerning the criteria by Equation (16).

$$\begin{array}{lllllll}
\delta_1^1 = 3.1416 & \delta_2^1 = 3.0944 & \delta_3^1 = 2.9193 & \delta_1^2 = 2.8273 & \delta_2^2 = 2.8637 & \delta_3^2 = 3.1952 \\
\delta_1^3 = 3.2130 & \delta_2^3 = 3.1638 & \delta_3^3 = 3.2932 & \delta_1^4 = 2.7397 & \delta_2^4 = 3.2373 & \delta_3^4 = 2.5080 \\
\delta_1^5 = 3.2104 & \delta_2^5 = 2.6719 & \delta_3^5 = 2.6907 & \delta_1^6 = 2.9828 & \delta_2^6 = 2.9625 & \delta_3^6 = 3.1707
\end{array}$$

Step 4: Based on Equation (17), the weight of each DM can be obtained.

$$\begin{array}{llll}
\omega_1^1 = \frac{\delta_1^1}{\delta_1^1+\delta_2^1+\delta_3^1} = 0.3431 & \omega_2^1 = \frac{\delta_2^1}{\delta_1^1+\delta_2^1+\delta_3^1} = 0.3380 & \omega_3^1 = \frac{\delta_3^1}{\delta_1^1+\delta_2^1+\delta_3^1} = 0.3189 \\
\omega_1^2 = \frac{\delta_1^2}{\delta_1^2+\delta_2^2+\delta_3^2} = 0.3182 & \omega_2^2 = \frac{\delta_2^2}{\delta_1^2+\delta_2^2+\delta_3^2} = 0.3223 & \omega_3^2 = \frac{\delta_3^2}{\delta_1^2+\delta_2^2+\delta_3^2} = 0.3596 \\
\omega_1^3 = \frac{\delta_1^3}{\delta_1^3+\delta_2^3+\delta_3^3} = 0.3323 & \omega_2^3 = \frac{\delta_2^3}{\delta_1^3+\delta_2^3+\delta_3^3} = 0.3272 & \omega_3^3 = \frac{\delta_3^3}{\delta_1^3+\delta_2^3+\delta_3^3} = 0.3406 \\
\omega_1^4 = \frac{\delta_1^4}{\delta_1^4+\delta_2^4+\delta_3^4} = 0.3229 & \omega_2^4 = \frac{\delta_2^4}{\delta_1^4+\delta_2^4+\delta_3^4} = 0.3815 & \omega_3^4 = \frac{\delta_3^4}{\delta_1^4+\delta_2^4+\delta_3^4} = 0.2956 \\
\omega_1^5 = \frac{\delta_1^5}{\delta_1^5+\delta_2^5+\delta_3^5} = 0.3745 & \omega_2^5 = \frac{\delta_2^5}{\delta_1^5+\delta_2^5+\delta_3^5} = 0.3117 & \omega_3^5 = \frac{\delta_3^5}{\delta_1^5+\delta_2^5+\delta_3^5} = 0.3139 \\
\omega_1^6 = \frac{\delta_1^6}{\delta_1^6+\delta_2^6+\delta_3^6} = 0.3272 & \omega_2^6 = \frac{\delta_2^6}{\delta_1^6+\delta_2^6+\delta_3^6} = 0.3250 & \omega_3^6 = \frac{\delta_3^6}{\delta_1^6+\delta_2^6+\delta_3^6} = 0.3478
\end{array}$$

5.2.2. Determine the Criteria Weights Using GBWM Method

In this section, the weight of each DM calculated in the process of Section 5.2.1 is utilized to determine the criteria weights. For convenience, we aggregated each DM's weights associated with the criterion $C_\tau (\tau = 1, 2, \ldots, n)$ into the comprehensive Equation (30).

$$\omega_\kappa = \frac{1}{n} \sum_{\tau=1}^{n} \omega_\kappa^\tau, \ \kappa = 1, 2, \ldots, \eta. \tag{30}$$

Then, we can gain three DMs' comprehensive weights $\omega_1 = 0.3364$, $\omega_2 = 0.3343$, $\omega_3 = 0.3294$.

Step 1: Determine a collection of criteria $C_\tau (\tau = 1, 2, \ldots, 6)$ for decision making, and the detailed information can be introduced in Table 2.

Step 2: Identify the best criterion C_B and the worst criterion C_W, respectively.

In our case, the specific expert determines that price of agricultural material (C_1) and speed of response to requirements (C_4) are C_B and C_W, respectively.

Step 3: Utilize the scale numbers between 1 to 9 to determine the preference of C_B over all the other criteria, simplified as BTO vector $\overline{A}_B = (\overline{\alpha}_{B1}, \overline{\alpha}_{B2}, \ldots, \overline{\alpha}_{Bn})$, which is shown in Table 3.

Step 4: Utilize the scale numbers between 1 to 9 to determine the preference of all the criteria over C_W, simplified as the OTW vector $\overline{A}_W = (\overline{\alpha}_{1W}, \overline{\alpha}_{2W}, \ldots, \overline{\alpha}_{nW})^T$, which is listed in Table 4.

Step 5: Obtain the optimal weights $\omega^* = \left(\omega_1^*, \omega_2^*, \ldots, \omega_n^*\right)$, the model in Equation (21) is presented as follows:

$$\mathrm{Min}(0.3364\varepsilon_1 + 0.3343\varepsilon_2 + 0.3294\varepsilon_3)$$

$$St.$$

$$\left|\frac{\omega_1}{\omega_2} - 2\right| \le \varepsilon_1, \left|\frac{\omega_1}{\omega_2} - 3\right| \le \varepsilon_2, \left|\frac{\omega_1}{\omega_2} - 2\right| \le \varepsilon_3, \left|\frac{\omega_1}{\omega_3} - 4\right| \le \varepsilon_1, \left|\frac{\omega_1}{\omega_3} - 5\right| \le \varepsilon_2, \left|\frac{\omega_1}{\omega_3} - 3\right| \le \varepsilon_3,$$

$$\left|\frac{\omega_6}{\omega_4} - 6\right| \le \varepsilon_1, \left|\frac{\omega_6}{\omega_4} - 5\right| \le \varepsilon_2, \left|\frac{\omega_6}{\omega_4} - 6\right| \le \varepsilon_3$$

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 + \omega_6 = 1$$

$$\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6 \ge 0.$$

Thus, the optimal weights can be derived as:

$$\omega_1^* = 0.2601,\ \omega_2^* = 0.2059,\ \omega_3^* = 0.1115,\ \omega_4^* = 0.0325,\ \omega_5^* = 0.1950,\ \omega_6^* = 0.1950 \text{ and } \varepsilon_1^* = 1.6667,\ \varepsilon_2^* = \varepsilon_3^* = 2.6667.$$

Note, that the above model was disposed by LINGO or MATLAB software.

Table 2. The detailed information concerning each criterion C_τ [42,43].

Criterion	Content	Explanation
C_1	Price of green agricultural product	Price is regarded as the essential element in the green agricultural product supplier selection, it determines the profit of the final product.
C_2	Quality of green agricultural product	Producers, as well as consumers, pay high attention to quality. Actively improving the quality of green agricultural product to meet the high standards, thus, raises the evaluation of the product.
C_3	Production capacity and technology	Production capacity and technology plays a significant role in the production efficiency and level, thus, effectively suppliers should respond to the transformation in customer demands.
C_4	Delivery	In terms of delivery, determine whether the supplier has sufficient production capacity, sufficient human resources, and the potential to expand capacity.
C_5	Environmental management	This criterion is closely related to the environment, including environmental certification, implementation and operation, environmental planning, as well as environmental policies.
C_6	Design for environment	It mainly measures five sections, which are: recycle, reuse, remanufacture, disassembly, disposal.

Table 3. Pairwise comparison of the best-to-others BTO vector.

	$\overline{\boldsymbol{\alpha}}_{12}$	$\overline{\boldsymbol{\alpha}}_{13}$	$\overline{\boldsymbol{\alpha}}_{14}$	$\overline{\boldsymbol{\alpha}}_{15}$	$\overline{\boldsymbol{\alpha}}_{16}$
DM_1	2	4	9	3	3
DM_2	3	5	8	4	3
DM_3	2	3	8	3	4

Table 4. Pairwise comparison of the others-to-worst (OTW) vector.

	$\bar{\alpha}_{24}$	$\bar{\alpha}_{34}$	$\bar{\alpha}_{54}$	$\bar{\alpha}_{64}$
DM_1	8	4	7	6
DM_2	7	5	7	5
DM_3	7	4	6	6

5.2.3. Ranking by the Improved PROMETHEE II Method

According to the above analysis, the aggregated comprehensive evaluation matrix by the three DMs is listed in Table 5 ($q = 3$).

Table 5. The aggregated comprehensive evaluation matrix.

	C_1	C_2	C_3	C_4	C_5	C_6
α_1	(0.702, 0.470)	(0.806, 0.552)	(0.847, 0.520)	(0.754, 0.299)	(0.795, 0.364)	(0.681, 0.636)
α_2	(0.809, 0.296)	(0.840, 0.362)	(0.620, 0.473)	(0.825, 0.651)	(0.805, 0.356)	(0.882, 0.313)
α_3	(0.682, 0.414)	(0.834, 0.477)	(0.625, 0.314)	(0.883, 0.302)	(0.821, 0.414)	(0.795, 0.259)
α_4	(0.834, 0.340)	(0.769, 0.298)	(0.623, 0.689)	(0.775, 0.541)	(0.789, 0.428)	(0.796, 0.568)

Then, the detailed processes of the improved PROMETHEE II method are as follows:

Step 1: Normalize the original assessment decision matrix $X = [\chi_{\varsigma\tau}]_{m\times n}$ to $\widetilde{X} = [\widetilde{\chi}_{\varsigma\tau}]_{m\times n}$.

Due to the fact that C_1 belongs to the cost-type input, other criteria are all benefit-type inputs, then the transformation form is depicted in Table 6.

Table 6. The transformation $\widetilde{X}$ of comprehensive evaluation matrix.

	C_1	C_2	C_3	C_4	C_5	C_6
α_1	(0.470, 0.702)	(0.806, 0.552)	(0.847, 0.520)	(0.754, 0.299)	(0.795, 0.364)	(0.681, 0.636)
α_2	(0.296, 0.809)	(0.840, 0.362)	(0.620, 0.473)	(0.825, 0.651)	(0.805, 0.356)	(0.882, 0.313)
α_3	(0.414, 0.682)	(0.834, 0.477)	(0.625, 0.314)	(0.883, 0.302)	(0.821, 0.414)	(0.795, 0.259)
α_4	(0.340, 0.834)	(0.769, 0.298)	(0.623, 0.689)	(0.775, 0.541)	(0.788, 0.428)	(0.796, 0.568)

Step 2: Calculate the deviations $d_\tau(\tau = 1, 2, \ldots, n)$ based on Equation (24) (suppose $p = 2$, $q = 3$ and $C = 100$), which are listed as:

$$d_1(\alpha_1,\alpha_2) = 0.1617, d_2(\alpha_1,\alpha_2) = -0.0341, d_3(\alpha_1,\alpha_2) = 0.3804, d_4(\alpha_1,\alpha_2) = -0.1983, d_5(\alpha_1,\alpha_2) = -0.0183, d_6(\alpha_1,\alpha_2) = -0.3280,$$
$$d_1(\alpha_1,\alpha_3) = -0.0373, d_2(\alpha_1,\alpha_3) = -0.0385, d_3(\alpha_1,\alpha_3) = 0.3949, d_4(\alpha_1,\alpha_3) = -0.2608, d_5(\alpha_1,\alpha_3) = -0.0564, d_6(\alpha_1,\alpha_3) = -0.1410,$$
$$d_1(\alpha_1,\alpha_4) = 0.2160, d_2(\alpha_1,\alpha_4) = 0.1103, d_3(\alpha_1,\alpha_4) = 1.0291, d_4(\alpha_1,\alpha_4) = -0.0735, d_5(\alpha_1,\alpha_4) = 0.0033, d_6(\alpha_1,\alpha_4) = -0.1889,$$
$$d_1(\alpha_2,\alpha_1) = -0.1617, d_2(\alpha_2,\alpha_1) = 0.0341, d_3(\alpha_2,\alpha_1) = -0.3804, d_4(\alpha_2,\alpha_1) = 0.1983, d_5(\alpha_2,\alpha_1) = 0.0183, d_6(\alpha_2,\alpha_1) = 0.3280,$$
$$d_1(\alpha_2,\alpha_3) = -0.1991, d_2(\alpha_2,\alpha_3) = -0.0044, d_3(\alpha_2,\alpha_3) = 0.0145, d_4(\alpha_2,\alpha_3) = -0.0625, d_5(\alpha_2,\alpha_3) = -0.0380, d_6(\alpha_2,\alpha_3) = 0.1870,$$
$$d_1(\alpha_2,\alpha_4) = 0.0543, d_2(\alpha_2,\alpha_4) = 0.1444, d_3(\alpha_2,\alpha_4) = 0.6487, d_4(\alpha_2,\alpha_4) = 0.1248, d_5(\alpha_2,\alpha_4) = 0.0217, d_6(\alpha_2,\alpha_4) = 0.1391,$$
$$d_1(\alpha_3,\alpha_1) = 0.0373, d_2(\alpha_3,\alpha_1) = 0.0385, d_3(\alpha_3,\alpha_1) = -0.3949, d_4(\alpha_3,\alpha_1) = 0.2608, d_5(\alpha_3,\alpha_1) = 0.0564, d_6(\alpha_3,\alpha_1) = 0.1410,$$
$$d_1(\alpha_3,\alpha_2) = 0.1991, d_2(\alpha_3,\alpha_2) = 0.0044, d_3(\alpha_3,\alpha_2) = -0.0145, d_4(\alpha_3,\alpha_2) = 0.0625, d_5(\alpha_3,\alpha_2) = 0.0380, d_6(\alpha_3,\alpha_2) = -0.1870,$$
$$d_1(\alpha_3,\alpha_4) = 0.2533, d_2(\alpha_3,\alpha_4) = 0.1488, d_3(\alpha_3,\alpha_4) = 0.6342, d_4(\alpha_3,\alpha_4) = 0.1874, d_5(\alpha_3,\alpha_4) = 0.0597, d_6(\alpha_3,\alpha_4) = -0.0479,$$
$$d_1(\alpha_4,\alpha_1) = -0.2160, d_2(\alpha_4,\alpha_1) = -0.1103, d_3(\alpha_4,\alpha_1) = -1.0291, d_4(\alpha_4,\alpha_1) = 0.0735, d_5(\alpha_4,\alpha_1) = -0.0033, d_6(\alpha_4,\alpha_1) = 0.1889,$$
$$d_1(\alpha_4,\alpha_2) = -0.0543, d_2(\alpha_4,\alpha_2) = -0.1444, d_3(\alpha_4,\alpha_2) = -0.6487, d_4(\alpha_4,\alpha_2) = -0.1248, d_5(\alpha_4,\alpha_2) = -0.0217, d_6(\alpha_4,\alpha_2) = -0.1391,$$

Step 3: Define the preference function $p_\tau(\alpha_a, \alpha_b)$.

As mentioned above, $p_\tau(\alpha_a, \alpha_b) = d_\tau(\alpha_a, \alpha_b)$ is actively defined, so the detailed process is omitted here.

Step 4: Determine the global preference index $\Pi(\alpha_a, \alpha_b)$ by Equation (26), and the associated weights $\omega_\tau = (0.2601, 0.2059, 0.1115, 0.0325, 0.1950, 0.1950)$ are determined by the GBWM, shown in Table 7.

Table 7. The global preference index $\Pi(\alpha_a, \alpha_b)$.

$\Pi(\alpha_a,\alpha_b)$	α_1	α_2	α_3	α_4
α_1		0.0034	−0.0206	0.1550
α_2	−0.0034		−0.0240	0.1516
α_3	0.0206	0.0240		0.1756
α_4	−0.1550	−0.1516	−0.1756	

Step 5: Based on Equations (27) and (28), aggregate $\Pi(\alpha_a, \alpha_b)$ into the positive $\varphi^+(\alpha_a)$ and negative $\varphi^-(\alpha_a)$ outranking flows, the results are as follows:

$$\varphi^+(\alpha_1) = 0.0460, \varphi^-(\alpha_1) = -0.0460, \varphi^+(\alpha_2) = 0.0414, \varphi^-(\alpha_2) = -0.0414,$$
$$\varphi^+(\alpha_3) = 0.0734, \varphi^-(\alpha_3) = -0.0734, \varphi^+(\alpha_4) = -0.1607, \varphi^-(\alpha_4) = 0.1607.$$

Step 6: Finally, rank the alternatives by calculating the comprehensive net flow $\varphi(\alpha_a)$.

$$\varphi(\alpha_1) = 0.0919,\ \varphi(\alpha_2) = 0.0827,\ \varphi(\alpha_3) = 0.1468,\ \varphi(\alpha_4) = -0.3214.$$

Then, the ranking result of all the alternatives is $\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$. Therefore, α_3 is the most desirable high-grade soybean supplier.

5.3. Comparative Analysis

5.3.1. Validity Analysis

To verify the availability of the improved GBWM-PROMETHEE II method, the novel method in [44] was utilized to solve the same study case.

For convenience, suppose $s = 1, t = 0.5$ and $q = 3$, then the final rankings of the feasible alternatives are depicted in the following Table. It is shown in Table 8 that the above technique [44] and our method can get same result as $\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$. So, it proves the proposed method is effective and available. In the following, some discussion will be given to further explain the superiority of our improved method.

Table 8. Ranking orders for different methods.

Methods	Ranking Values	Ranking Order
$q-ROFBM\ s = 1, t = 0.5$ [44]	$S(\alpha_1) = 0.2774, S(\alpha_2) = 0.2767,$ $S(\alpha_3) = 0.3612, S(\alpha_4) = 0.1598.$	$\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$
The proposed method	$\varphi(\alpha_1) = 0.0919, \varphi(\alpha_2) = 0.0827,$ $\varphi(\alpha_3) = 0.1468, \varphi(\alpha_4) = -0.3214.$	$\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$

5.3.2. Superiority of the Proposed Method

To illustrate the strengths of the improved GBWM-PROMETHEE II method vividly, several widespread methods were applied in solving the above practical case with the q-ROF information, including VIKOR [45] and TOPSIS [18]. The comparison results are depicted by the form of ranking orders as Table 9. (Suppose $q = 3$). As we can see from the Table 9, the rankings by utilizing three methods differ from the results by our method in this paper slightly. Meanwhile, for the sake of emphasizing the significance of the GBWM to derive each criterion weights, we further assigned the same importance degree directly to each criterion of the above-mentioned methods, then by means of

comparing the final rankings as Table 10 to analyze the reliability of determining criterion weights by GBWM.

Table 9. Comparison results with obtained criteria weights by GBWM.

Methods	Ranking Values	Ranking Order
VIKOR [45]	$S(\alpha_1) = 0.4257, S(\alpha_2) = 0.6372,$ $S(\alpha_3) = 0.5344, S(\alpha_4) = 0.4753.$ $R(\alpha_1) = 0.1672, R(\alpha_2) = 0.1647,$ $R(\alpha_3) = 0.1653, R(\alpha_4) = 0.2059.$ $Q(\alpha_1) = 0.0407, Q(\alpha_2) = 0.3333,$ $Q(\alpha_3) = 0.1809, Q(\alpha_4) = 0.7449.$	$\alpha_1, \alpha_2, \alpha_3$ are all the compromise solutions
TOPSIS [18]	$C(\alpha_1) = 0.6247, C(\alpha_2) = 0.3885,$ $C(\alpha_3) = 0.3583, C(\alpha_4) = 0.5406.$	$\alpha_1 \succ \alpha_4 \succ \alpha_2 \succ \alpha_3$
The proposed method	$\varphi(\alpha_1) = 0.0919, \varphi(\alpha_2) = 0.0827,$ $\varphi(\alpha_3) = 0.1468, \varphi(\alpha_4) = -0.3214.$	$\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$

Table 10. Comparison results with assigning the criteria weights.

Methods	Expected Values	Ranking Order
VIKOR [45] $\omega_1 = \omega_2 = \omega_3 =$ $\omega_4 = \omega_5 = \omega_6 = 0.1667$	$S(\alpha_1) = 0.4986, S(\alpha_2) = 0.5748,$ $S(\alpha_3) = 0.5913, S(\alpha_4) = 0.4641.$ $R(\alpha_1) = 0.1658, R(\alpha_2) = 0.1407,$ $R(\alpha_3) = 0.1656, R(\alpha_4) = 0.1667.$ $Q(\alpha_1) = 0.7355, Q(\alpha_2) = 0.2900,$ $Q(\alpha_3) = 0.9727, Q(\alpha_4) = 0.6667.$	α_1, α_2 are the compromise solutions
TOPSIS [18] $\omega_1 = \omega_2 = \omega_3 =$ $\omega_4 = \omega_5 = \omega_6 = 0.1667$	$C(\alpha_1) = 0.5350, C(\alpha_2) = 0.4605,$ $C(\alpha_3) = 0.3035, C(\alpha_4) = 0.5670.$	$\alpha_4 \succ \alpha_1 \succ \alpha_2 \succ \alpha_3$
The proposed method (obtained weights by GBWM)	$\varphi(\alpha_1) = 0.0919, \varphi(\alpha_2) = 0.0827,$ $\varphi(\alpha_3) = 0.1468, \varphi(\alpha_4) = -0.3214.$	$\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$

In the following, the analysis concerning the comparison of different methods is described in detail.

(i) Compare with the VIKOR method [45].

The VIKOR method [45] has the ability to select and rank from several alternatives in the face of the situation with conflicting criteria. However, from Table 9, we can conclude that this method cannot effectively distinguish the alternatives in our case. By means of calculating the values of S, R, and Q with respect to the four alternatives as well as the sorting rules, the ranking result can be gained, as $\alpha_1, \alpha_2, \alpha_3$ are all the compromise solutions. Nevertheless, the difference in the proposed method is providing a complete ranking order by comparing the values of the comprehensive net flow, as $\alpha_3 \succ \alpha_1 \succ \alpha_2 \succ \alpha_4$. In addition, when the weights were directly assigned to each criterion instead of obtained by means of the GBWM, the ranking result derived by the VIKOR also differed from our method, which is depicted in detail in Table 10. It can be easily concluded that α_1 and α_2 are the compromise solutions, so the VIKOR cannot select the optimal agricultural material supplier in the case. In other words, the ranking results obtained by the improved GBWM- PROMETHEE II in this paper are more forceful and reasonable.

(ii) Compare with the TOPSIS method [18].

The TOPSIS method considers the notion of similarity between each alternative and the ideal solution, as well as the negative ideal solution. From Table 9, the ranking based on the TOPSIS differed from the order obtained by the proposed method. This is mainly because the standard form of the TOPSIS is deterministic, while the improved GBWM-PROMETHEE II method in this paper considers the significance of pairwise comparisons, as well as the positive or negative evaluation information given by DMs. Moreover, from different orders shown in Table 10, by means of assigning the same

weight to each criterion directly in the TOPSIS method, we can acquire another weakness of the TOPSIS. That is, it does not consider uncertainty in weightings. Nevertheless, for deriving the reasonable weightings, our method attaches importance to DM's weights and relative preference degree for each criterion by utilizing the GBWM method.

According to the above analysis, we can summarize that the improved GBWM-PROMETHEE II method is more comprehensive as well as has more powerful aggregation capabilities than some other existing methods.

6. Conclusions

The decision-making problem concerning green agricultural product supplier selection plays an essential role in the management of firms, as it directly influences the business capacity and competitiveness of the agribusiness. In this paper, an improved GBWM-PROMETHEE II method was introduced under q-ROF environment to deal with the common MCDM problems. Firstly, the notion of generalized p-norm knowledge-based score function was proposed to compare any two q-ROFNs. Secondly, to rank the feasible alternatives, we improved the PROMETHEE II method by replacing original evaluation given by DMs with the p-norm knowledge-based score function. Moreover, the GBWM was reasonably utilized to derive each criterion weightings instead of assigning directly. Then, the proposed method was applied to solve the supplier selection for a green agricultural product deep processing industry in China. By comparing with other traditional methods, we found that the proposed method can provide us more forceful and reasonable ranking results effectively. When it comes to the limitations of this paper, it should integrate the theory with practice in more detailed way, that is, according to the practical application, how to utilize the obtained results to help the production sector. In particular, the industry of certain agri-food products in developing countries is still a challenge for us.

In future research, the proposed method can be widely applied to handle other classical MCDM problems with the existing fuzzy information. In addition, from the method point of view, several methods can also be extended to determine the criteria weightings, for instance, CCSD [46] and GRA [47].

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

Appendix A

Table A1. DMs' evaluation matrix concerning the criterion C_1.

	α_1	α_2	α_3	α_4
DM_1	$(0.2, 0.3)$	$(0.7, 0.3)$	$(0.2, 0.4)$	$(0.4, 0.4)$
DM_2	$(0.5, 0.4)$	$(0.3, 0.8)$	$(0.5, 0.3)$	$(0.6, 0.2)$
DM_3	$(0.3, 0.9)$	$(0.5, 0.1)$	$(0.2, 0.6)$	$(0.7, 0.5)$

Table A2. DMs' evaluation matrix concerning the criterion C_2.

	α_1	α_2	α_3	α_4
DM_1	$(0.3, 0.5)$	$(0.3, 0.4)$	$(0.8, 0.3)$	$(0.2, 0.4)$
DM_2	$(0.7, 0.4)$	$(0.5, 0.6)$	$(0.1, 0.7)$	$(0.3, 0.1)$
DM_3	$(0.5, 0.8)$	$(0.8, 0.2)$	$(0.6, 0.5)$	$(0.7, 0.6)$

Table A3. DMs' evaluation matrix concerning the criterion C_3.

	α_1	α_2	α_3	α_4
DM_1	$(0.6, 0.5)$	$(0.3, 0.3)$	$(0.2, 0.3)$	$(0.2, 0.6)$
DM_2	$(0.5, 0.7)$	$(0.1, 0.7)$	$(0.1, 0.2)$	$(0.4, 0.6)$
DM_3	$(0.7, 0.4)$	$(0.3, 0.5)$	$(0.4, 0.5)$	$(0.1, 0.9)$

Table A4. DMs' evaluation matrix concerning the criterion C_4.

	α_1	α_2	α_3	α_4
DM_1	$(0.1, 0.3)$	$(0.3, 0.8)$	$(0.5, 0.1)$	$(0.7, 0.3)$
DM_2	$(0.7, 0.2)$	$(0.6, 0.8)$	$(0.9, 0.4)$	$(0.2, 0.6)$
DM_3	$(0.2, 0.5)$	$(0.7, 0.4)$	$(0.2, 0.7)$	$(0.4, 0.9)$

Table A5. DMs' evaluation matrix concerning the criterion C_5.

	α_1	α_2	α_3	α_4
DM_1	$(0.4, 0.2)$	$(0.7, 0.3)$	$(0.5, 0.5)$	$(0.6, 0.3)$
DM_2	$(0.5, 0.3)$	$(0.5, 0.8)$	$(0.1, 0.7)$	$(0.3, 0.4)$
DM_3	$(0.6, 0.9)$	$(0.2, 0.2)$	$(0.8, 0.2)$	$(0.5, 0.7)$

Table A6. DMs' evaluation matrix concerning the criterion C_6.

	α_1	α_2	α_3	α_4
DM_1	$(0.2, 0.9)$	$(0.8, 0.3)$	$(0.4, 0.2)$	$(0.4, 0.5)$
DM_2	$(0.2, 0.4)$	$(0.5, 0.5)$	$(0.6, 0.1)$	$(0.5, 0.6)$
DM_3	$(0.5, 0.7)$	$(0.7, 0.2)$	$(0.5, 0.8)$	$(0.6, 0.6)$

Appendix B

Table A7. The similarity degree $z^1_{\kappa\varsigma}$ concerning the criterion C_1.

	α_1	α_2	α_3	α_4
DM_1	0.7314	0.9650	0.7880	0.6572
DM_2	0.8705	0.5637	0.8801	0.7801
DM_3	0.4509	0.7334	0.8155	0.9195

Table A8. The similarity degree $z^2_{\kappa\varsigma}$ concerning the criterion C_2.

	α_1	α_2	α_3	α_4
DM_1	0.6289	0.5820	0.9324	0.6840
DM_2	0.8815	0.7161	0.5932	0.6728
DM_3	0.6852	0.9477	0.7547	0.8075

Table A9. The similarity degree $z^3_{\kappa\varsigma}$ concerning the criterion C_3.

	α_1	α_2	α_3	α_4
DM_1	0.7738	0.8276	0.8420	0.7696
DM_2	0.7278	0.7922	0.8244	0.8194
DM_3	0.8549	0.8890	0.9021	0.6471

Table A10. The similarity degree $z^4_{\kappa\varsigma}$ concerning the criterion C_4.

	α_1	α_2	α_3	α_4
DM_1	0.6659	0.6632	0.5515	0.8591
DM_2	0.9809	0.7691	0.8099	0.6774
DM_3	0.7100	0.7682	0.5208	0.5089

Table A11. The similarity degree $z^5_{\kappa\varsigma}$ concerning the criterion C_5.

	α_1	α_2	α_3	α_4
DM_1	0.7003	0.9547	0.7018	0.8537
DM_2	0.7722	0.5978	0.6106	0.6913
DM_3	0.3770	0.6125	0.9364	0.7648

Table A12. The similarity degree $z^6_{\kappa\varsigma}$ concerning the criterion C_6.

	α_1	α_2	α_3	α_4
DM_1	0.5858	0.9805	0.7218	0.6947
DM_2	0.6570	0.6333	0.8698	0.8024
DM_3	0.9090	0.8013	0.5690	0.8913

References

1. Liu, G.; Su, S.S.; Feng, Q. Performance evaluation system for agricultural products green supply chain. In *International Conference on Mechatronics and Intelligent Robotics*; Springer: Singapore, 2019; pp. 423–429.
2. Opara, L.U. Traceability in agriculture and food supply chain: A review of basic concepts, technological implications, and future prospects. *J. Food Agric. Environ.* **2003**, *1*, 101–106.
3. Fernandez, A.; Waghmare, A.; Tripathi, S. *Agricultural Supply Chain Using Blockchain*; Springer: Singapore, 2020; pp. 127–134.
4. Beske, P.; Land, A.; Seuring, S. Sustainable supply chain management practices and dynamic capabilities in the food industry: A critical analysis of the literature. *Int. J. Prod. Econ.* **2014**, *152*, 131–143. [CrossRef]
5. Bondoc, I. European regulation in the veterinary sanitary and food safety area, part one: The role of european institutions in laying down and passing laws specific to the veterinary sanitary and food safety area. In *European Policies on the Safety of Food Products and the Protection of Consumer Interests: A 2007 Retrospective*; Universul Juridic: București, Romania, 2016; pp. 2–15.
6. Cheng, W.; Appolloni, A.; D'Amato, A.; Zhu, Q. Green public procurement, missing concepts, and future trends–A critical review. *J. Clean. Prod.* **2018**, *176*, 770–784. [CrossRef]
7. Appolloni, A.; D'Amato, A.; Cheng, W. Is public procurement going green? Experiences and open issues. SSRN Electron. *J. Clean. Prod.* **2011**. [CrossRef]
8. Goswami, M.D.A.; Habibi, M.K.K.; Daultani, Y. Examining freight performance of third-party logistics providers within the automotive industry in India: An environmental sustainability perspective. *Int. J. Prod. Res.* **2020**, 1–28. [CrossRef]
9. De, A.; Mogale, D.G.; Zhang, M.; Pratap, S.; Kumar, S.K.; Huang, G.Q. Multi-period multi-echelon inventory transportation problem considering stakeholders behavioural tendencies. *Int. J. Prod. Econ.* **2020**, *225*, 107566. [CrossRef]
10. De, A.; Choudhary, A.; Turkay, M.; Tiwari, M.K. Bunkering policies for a fuel bunker management problem for liner shipping networks. *Eur. J. Oper. Res.* **2019**. [CrossRef]
11. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
12. Krassimir, T.A.; Parvathi, R. Intuitionistic fuzzy sets. *Fuzzy Sets Syst.* **1986**, *20*, 87–96.
13. Yager, R.R. Pythagorean membership grades in multicriteria decision making. *IEEE Trans. Fuzzy Syst.* **2013**, *22*, 958–965. [CrossRef]
14. Yager, R.R. Generalized orthopair fuzzy sets. *IEEE Trans. Fuzzy Syst.* **2017**, *25*, 1222–1230. [CrossRef]
15. Liu, Z.M.; Wang, S.; Liu, P.D. Multiple attribute group decision making based on q-rung orthopair fuzzy Heronian mean operators. *Int. J. Intell. Syst.* **2018**, *33*, 2341–2363. [CrossRef]

16. Liu, P.D.; Wang, Y. Intuitionistic fuzzy interaction hamy mean operators and their application to multi-attribute group decision making. *Group Decis. Negot.* **2019**, *28*, 197–232. [CrossRef]
17. Liu, Z.M.; Zhao, X.L.; Li, L.; Wang, X.Y.; Wang, D.; Liu, P.D. Selecting a public service outsourcer based on the improved ELECTRE II method with unknown weight information under a double hierarchy hesitant linguistic environment. *Sustainability* **2020**, *12*, 2315. [CrossRef]
18. Lei, F.; Wei, G.; Gao, H.; Wu, J.; Wei, C. TOPSIS method for developing supplier selection with probabilistic linguistic information. *Int. J. Fuzzy Syst.* **2020**, *22*, 1–11. [CrossRef]
19. Vincke, J.P.; Brans, P. A preference ranking organization method. The PROMETHEE method for MCDM. *Manage. Sci.* **1985**, *31*, 647–656.
20. Fei, L.; Deng, Y.; Hu, Y. DS-VIKOR: A new multi-criteria decision-making method for supplier selection. *Int. J. Fuzzy Syst.* **2019**, *21*, 157–175. [CrossRef]
21. Wang, T.K.; Zhang, Q.; Chong, H.Y.; Wang, X. Integrated supplier selection framework in a resilient construction supply chain: An approach via analytic hierarchy process (AHP) and grey relational analysis (GRA). *Sustainability* **2017**, *9*, 289. [CrossRef]
22. Hajikhani, A.; Khalilzadeh, M.; Sadjadi, S.J. A fuzzy multi-objective multi-product supplier selection and order allocation problem in supply chain under coverage and price considerations: An urban agricultural case study. *Sci. Iran* **2018**, *25*, 431–449. [CrossRef]
23. Saaty, T.L. Decision making for leaders. *IEEE Trans. Syst. Man Cybern.* **1985**, *3*, 450–452. [CrossRef]
24. Rezaei, J. Best-worst multi-criteria decision-making method. *Omega* **2015**, *53*, 49–57. [CrossRef]
25. Abadi, F.; Sahebi, I.; Arab, A.; Alavi, A.; Karachi, H. Application of best-worst method in evaluation of medical tourism development strategy. *Decis. Sci. Lett.* **2018**, *7*, 77–86. [CrossRef]
26. Safarzadeh, S.; Khansefid, S.; Barzoki, M.R. A group multi-criteria decision-making based on best-worst method. *Comput. Ind. Eng.* **2018**, *126*, 111–121. [CrossRef]
27. Deng, X.; Hu, Y.; Deng, Y.; Mahadevan, S. Supplier selection using AHP methodology extended by D numbers. *Expert Syst. Appl.* **2014**, *41*, 156–167. [CrossRef]
28. Kara, M.; Fırat, S. Supplier risk assessment based on best-worst method and k-means clustering: A case study. *Sustainability* **2018**, *10*, 1066. [CrossRef]
29. Krishankumar, R.; Ravichandran, K.S.; Saeid, A.B. A new extension to PROMETHEE under intuitionistic fuzzy environment for solving supplier selection problem with linguistic preferences. *Appl. Soft Comput.* **2017**, *60*, 564–576.
30. Adalı, E.; Işık, A.; Kundakcı, K. An alternative approach based on Fuzzy PROMETHEE method for the supplier selection problem. *Uncertain Supply Chain Manag.* **2016**, *4*, 183–194. [CrossRef]
31. Awasthi, A.; Govindan, K.; Gold, S. Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach. *Int. J. Prod. Econ.* **2018**, *195*, 106–117. [CrossRef]
32. Jain, V.; Sangaiah, A.K.; Sakhuja, S.; Thoduka, N.; Aggarwal, R. Supplier selection using fuzzy AHP and TOPSIS: A case study in the Indian automotive industry. *Neural Comput. Appl.* **2018**, *29*, 555–564. [CrossRef]
33. Lu, J.; Wei, C.; Wu, J.; Wei, G. TOPSIS method for probabilistic linguistic magdm with entropy weight and its application to supplier selection of new agricultural machinery products. *Entropy* **2019**, *21*, 953. [CrossRef]
34. Cheraghalipour, A.; Paydar, M.M.; Keshteli, M.H. Applying a hybrid BWM-VIKOR approach to supplier selection: A case study in the Iranian agricultural implements industry. *Int. J. Appl. Decis. Sci.* **2018**, *11*, 274–301. [CrossRef]
35. Wang, B.; Song, J.; Ren, J.; Li, K.; Duan, H.; Wang, X.E. Selecting sustainable energy conversion technologies for agricultural residues: A fuzzy AHP-VIKOR based prioritization from life cycle perspective. *Resour. Conserv. Recycl.* **2019**, *142*, 78–87. [CrossRef]
36. Liu, P.D.; Wang, P. Some q-rung orthopair fuzzy aggregation operators and their applications to multiple-attribute decision making. *Int. J. Intell. Syst.* **2018**, *33*, 259–280. [CrossRef]
37. Liu, Z.; Liu, P.; Liang, X. Multiple attribute decision-making method for dealing with heterogeneous relationship among attributes and unknown attribute weight information under q-rung orthopair fuzzy environment. *Int. J. Intell. Syst.* **2018**, *33*, 1900–1928. [CrossRef]
38. Wei, G.; Gao, H.; Wei, Y. Some q-rung orthopair fuzzy Heronian mean operators in multiple attribute decision making. *Int. J. Intell. Syst.* **2018**, *33*, 1426–1458. [CrossRef]
39. Peng, X.; Dai, J.; Garg, H. Exponential operation and aggregation operator for q-rung orthopair fuzzy set and their decision-making method with a new score function. *Int. J. Intell. Syst.* **2018**, *33*, 2255–2282. [CrossRef]

40. Nguyen, H. A Generalized p-norm knowledge-based score function for interval-valued intuitionistic fuzzy set in decision making. *IEEE Trans. Fuzzy Syst.* **2019**, *28*, 409–423. [CrossRef]
41. Ju, Y. A new method for multiple criteria group decision making with incomplete weight information under linguistic environment. *Appl. Math. Model.* **2014**, *38*, 5256–5268. [CrossRef]
42. Ristono, A.; Santoso, P.B.; Tama, I.P. A literature review of design of criteria for supplier selection. *J. Ind. Eng. Manag.* **2018**, *11*, 680–696.
43. Konys, A. Green supplier selection criteria: From a literature review to a comprehensive knowledge base. *Sustainability* **2019**, *11*, 4208. [CrossRef]
44. Liu, P.D.; Liu, J.L. Some q-rung orthopai fuzzy Bonferroni mean operators and their application to multi-attribute group decision making. *Int. J. Intell. Syst.* **2018**, *33*, 315–347. [CrossRef]
45. Kumar, A.; Aswin, A.; Gupta, H. Evaluating green performance of the airports using hybrid BWM and VIKOR methodology. *Tour. Manag.* **2020**, *76*, 103941. [CrossRef]
46. Wang, Y.M.; Luo, Y. Integration of correlations with standard deviations for determining attribute weights in multiple attribute decision making. *Math. Comp. Model.* **2010**, *51*, 1–12. [CrossRef]
47. Wei, G.; Lu, J.; Wei, C.; Wu, J. Probabilistic linguistic GRA method for multiple attribute group decision making. *J. Intell. Fuzzy Syst.* **2020**, *38*, 1–12. [CrossRef]