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Green Suppliers Performance Evaluation in Belt and Road Using Fuzzy Weighted Average with Social Media Information

Kuo-Ping Lin ^{1,2,*}, Kuo-Chen Hung ³, Yu-Ting Lin ¹ and Yao-Hung Hsieh ⁴

¹ Department of Information Management, Lunghwa University of Science and Technology, Taoyuan 33306, Taiwan; lin716007@gmail.com

² Institute of Innovation and Circular Economy, Asia University, Taichung 41354, Taiwan

³ Department of Computer Science and Information Management, Hungkuang University, Taichung 43302, Taiwan; kuochen.hung@msa.hinet.net

⁴ Department of Interior Design, China University of Technology, Taipei 11695, Taiwan; sayoho@cute.edu.tw

* Correspondence: kplin@mail.lhu.edu.tw; Tel.: +886-2-82093211 (ext. 6329)

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Abstract: A decision model for selecting a suitable supplier is a key to reducing the environmental impact in green supply chain management for high-tech companies. Traditional fuzzy weight average (FWA) adopts linguistic variable to determine weight by experts. However, the weights of FWA have not considered the public voice, meaning the viewpoints of consumers in green supply chain management. This paper focuses on developing a novel decision model for green supplier selection in the One Belt and One Road (OBOR) initiative through a fuzzy weighted average approach with social media. The proposed decision model uses the membership grade of the criteria and sub-criteria and its relative weights, which consider the volume of social media, to establish an analysis matrix of green supplier selection. Then, the proposed fuzzy weighted average approach is considered as an aggregating tool to calculate a synthetic score for each green supplier in the Belt and Road initiative. The final score of the green supplier is ordered by a non-fuzzy performance value ranking method to help the consumer make a decision. A case of green supplier selection in the light-emitting diode (LED) industry is used to demonstrate the proposed decision model. The findings demonstrate (1) the consumer's main concerns are the "Quality" and "Green products" in LED industry, hence, the ranking of suitable supplier in FWA with social media information model obtained the difference result with tradition FWA; (2) OBOR in the LED industry is not fervently discussed in searches of Google and Twitter; and (3) the FWA with social media information could objectively analyze the green supplier selection because the novel model considers the viewpoints of the consumer.

Keywords: green supplier; fuzzy weighted average; social media

1. Introduction

The One Belt One Road (OBOR) initiative was proposed to build a Silk Road Economic Zone and Maritime Silk Road in the 21st century. The OBOR aims to connect the Asian-Pacific Economic Area with the Euro Economic Area by building up two maritime routes. The initiative provides a blueprint of a strong integration of China into the world economy and represents the commitment of the Chinese government to a more open economy [1]. The strategy is formed at a critical point in China's economic transformation. This study investigates green supplier selection in the OBOR initiative. Environmental awareness should also be considered in the OBOR's strategy.

Today, enterprises pay more and more attention to environmental issues in all of their administrative activities since environmental issues have effects in almost all parts of our society [2].

Green supply chain management (GSCM) has placed emphasis on supply chain managers and practitioners such as [3–5]. GSCM integrates environmental factors into supply chain management, product design, and material purchasing [6–10]. It is important to objectively analyze the factors that influence green supply chain management by decision-making methods. Therefore, an effective decision model for green supplier selection is very important in green supply chain management. Kuo et al. [11] integrated an artificial neural network (ANN) and two multi-attribute decision analysis methods for green supplier selection. The proposed hybrid decision model adopted six dimensions: quality, cost, delivery, service, environment, and corporate social responsibility. In evaluating green suppliers' performances, the proposed hybrid decision model can obtain better power of noise-insensitivity and discrimination. Dobos and Vörösmarty [12] utilized data envelopment analysis (DEA) with the common weights analysis (CWA) method to green supplier selection. In these studies, green supplier selection has been widely studied, as it is an important means of managing supplier relationships.

Furthermore, the selection of green suppliers is limited by vague or ambiguous requirements. Fuzzy logic or fuzzy set theory has emerged as powerful means of performing quantitative evaluations and minimizing the imprecision associated with the selection of green suppliers. The fact that fuzzy sets and fuzzy numbers have the capacity to represent and manipulate imprecise parameters means that the process is more powerful and the results tend to be more credible [13–15]. A number of green supply chain studies have succeeded in integrating fuzzy numbers with decision models to facilitate the evaluation of performance among green suppliers [16–20]. This existing literature has well verified fuzzy decision models can provide information of greater credibility, and obtain highly effective in aggregating the views of experts.

Fuzzy weighted average (FWA) is one approach to fuzzy decision-making under multiple criteria. The FWA approach is a function of fuzzy numbers using interval arithmetic, which has proven useful for aggregation functions in management science and engineering. FWA has been applied in many decision-related fields, such as material substitution selection [21], location selection [22], flexible manufacturing system [23], military UAV selection [24], and office layouts [25]. However, the complexity of FWA increases exponentially with an increase in the number of criteria, which greatly limits its applicability. This is particularly evident today, when the emphasis is on obtaining accurate results despite an explosion in the availability of information.

The purpose of this research is to develop a decision model for decision-making in uncertain environments, one specifically tailored for managers in green supply chain management. In so doing, we developed an FWA with social media information, which is particularly important in today's internet environment. In the internet environment, social media information provides numerous possibilities for consumers and other stakeholders to voice their opinions [26]. Therefore, the voice of social media information can be considered to assist in decision-making [27,28]. This FWA with social media information model can expand its applicability to include cloud systems and even systems operating in real time. We then apply the proposed method to the selection of green suppliers in the LED industry. In a case study, the proposed FWA approach was shown to provide credible and efficient ranking results for decision-makers.

The remainder of this paper is organized as follows. Section 2 introduces the proposed FWA with social media information. Section 3 provides an illustrative case in which the proposed FWA with social media information is applied to the selection of green suppliers in the LED industry. Conclusions are drawn in Section 4.

2. FWA with Social Media Information

FWA was introduced in 1977 by [29]. Generally speaking, an FWA may be defined by obtaining the fuzzy (criteria) ratings, which adopts the fuzzy numbers (FNs). In this FWA with social media information, A_j , $j = 1, 2, \dots, m$, is alternative. C_{ji} , $i \in \{1, 2, \dots, n\}$ is sub-criteria, and W_i , $i \in \{1, 2, \dots, n\}$ is the fuzzy weightings. The Y_j for the objects is reached, which may be ranked with various

ranking algorithms by the outcomes of the proposed FWA method with social media information. In this study, the fuzzy weightings are changed, which considers social media information. This study used the web crawler technique to tune the fuzzy weighting. The crawlers take as input a number of starting application programming interfaces (APIs) in Twitter and Google searches. This API can be a list of key terms for training sets for learning crawlers and shows the search volume in Twitter or Google. Therefore, the meaning input key terms will be very important. The equation of FWA with social media information can be defined by

$$Y_j = f(C_{j1}, \dots, C_{ji}, \dots, C_{jn}, W_1 \times N_1, \dots, W_i \times N_i, \dots, W_n \times N_n) = \frac{\sum_{i=1}^n W_i \times N_i \times C_{ji}}{\sum_{i=1}^n W_i \times N_i}. \quad (1)$$

where $N_i = \frac{V_i}{\sum_{i=1}^n V_i}$ is normalization of term which is search volume (V_i) in social media.

A number of researchers have proposed appropriate methods for finding the FWA membership function Y_j [30–35].

3. Case Study: Green Supplier Selection in Belt and Road

Manufacturers should consider environmentally friendly operating processes because many countries' policies have set the environment protection standards. The sustainability of a manufacturer in the long term is a necessary issue in the LED industry. Manufacturers need a good decision model to evaluate the suppliers on their suitability, and the suppliers also need to consider environmentally friendly operating processes. Hence, this study presents a fuzzy weighted average with a social media information multiple criterion decision making method for evaluating green suppliers in LED industrial management.

Various materials in the current LED industry are procured for manufacturing LED production, and many components are produced in a variety of production processes. These components may be provided by different/substitute suppliers. Green supplier, which can provide environmentally friendly components, should be considered first. The novel FWA with social media information model is developed for decision making in selecting the most appropriate green supplier, and the decision model can also consider the One Belt and One Road in computing the fuzzy weights.

Figure 1 presents the framework of novel FWA with social media information. The procedures of crawlers include four steps, which are (1) inputting API: the Google and Twitter API are employed in the study; (2) extracting and placing: a queue set is generated through extracting and placing downloaded pages; (3) analyzing and reducing: downloaded information will be analyzed and reduced into the database, which adopts a stemming algorithm [36]; and (4) terminal condition: the desired periods are satisfied. In the following sections, criteria and weights with social media information for green supplier selection will be used to describe the green supplier selection process using the general ranking. The main steps for green supplier selection are described as follows:

- Step 1* Identifying the criteria for green supplier selection and normalizing the search volume in social media;
- Step 2* Computing the fuzzy weights with social media information of the sub-criteria;
- Step 3* Computing the aggregated fuzzy rating of sub-criteria;
- Step 4* Implementing the proposed FWA algorithm to compute the total fuzzy values of green suppliers from the fuzzy weights with social information and the criteria rating matrix;
- Step 5* Setting the rank order of green suppliers by defuzzified method.

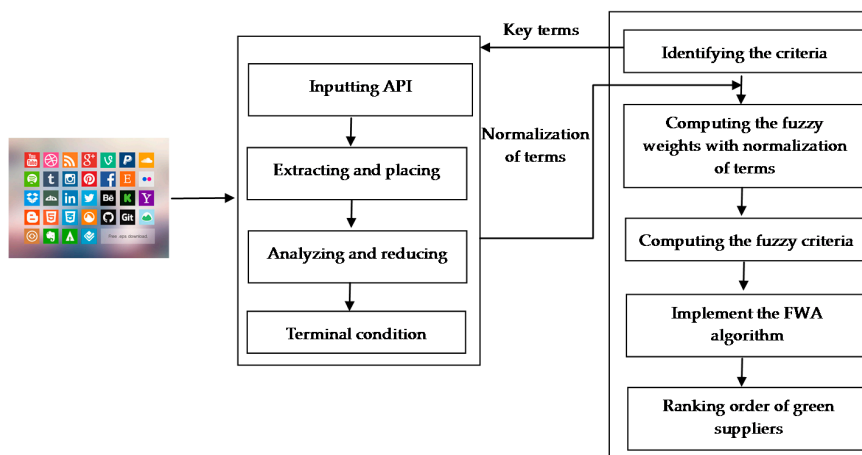


Figure 1. The framework of novel fuzzy weighted average (FWA) with social media information.

Step 1 Identifying the criteria for green supplier selection

This study applied six main criteria to the case of selecting green suppliers: “Quality”, “Technological capability”, “Pollution control”, “Environmental management”, “Green products”, and “Green competencies.” These criteria were adopted from the studies by [37–39]. Details of the main and sub-criteria are as follows (or see Figure 2):

- Quality (C_1) [37–39]: Factors with a direct influence on the quality of products, including the following sub-criteria: quality-related certificates (C_{11}), quality management capabilities (C_{12}), and handling of cases involving abnormal quality (C_{13}).
- Technological capability (C_2) [39]: Factors capable of facilitating the development of new products or processes of benefit to the firm, including the following sub-criteria: technology level (C_{21}), R&D capability (C_{22}), design capability (C_{23}), and pollution prevention capability (C_{24}).
- Pollution control (C_3) [39]: Factors that illustrate the ability of suppliers to control the pollution they produce, including the following sub-criteria: air emissions (C_{31}), wastewater (C_{32}), solid wastes (C_{33}), energy consumption (C_{34}), and the use of harmful materials (C_{35}).
- Environmental management (C_4) [37,38]: Factors that demonstrate the efforts taken by suppliers with regard to environmental management, including the following sub-criteria: environment-related certificates (C_{41}), continuous monitoring and regulatory compliance (C_{42}), internal control processes (C_{43}), and green process planning (C_{44}).
- Green products (C_5) [38,39]: Factors that demonstrate the efforts taken by suppliers to produce green products, including the following sub-criteria: recycling (C_{51}), green packaging (C_{52}), and the costs associated with component disposal (C_{53}).
- Green competencies (C_6) [37,39]: Factors that demonstrate the competencies of suppliers in improving green production, including the following sub-criteria: the use of materials capable of reducing the use of natural resources (C_{61}), the ability to alter processes and products with the aim of reducing the impact on the environment (C_{62}), social responsibility (C_{63}), and the ratio of green customers to total customers (C_{64}).

Table 1 shows the normalization of the search volume in social media. The input key terms include six main criteria, LED, and One Belt and One Road. In this study, social media adopts Google search and Twitter (covering the period from January to September 2017), which are popular and famous social media applications. Figure 3 shows the volume of key terms in Google search and Twitter. “Quality” + “LED” + “One Belt and One Road” can be searched in Google search. However, the input terms “Quality” + “LED” + “One Belt and One Road” could not be searched at any volume in Twitter, which may be the result of Twitter’s members not being interested in discussing the three terms. In Twitter, the members are consumers who only discuss the quality issue in the LED industry.

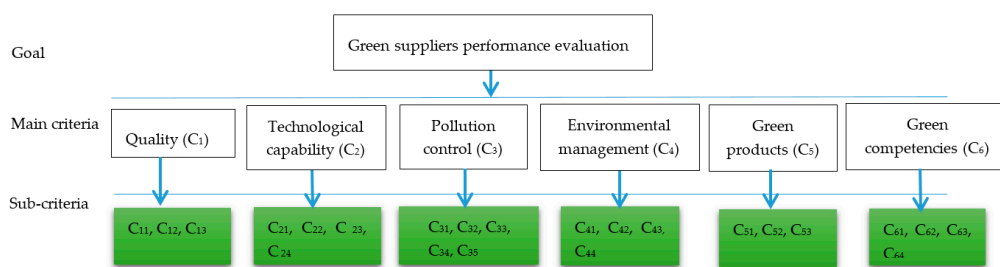


Figure 2. The criteria for green supplier selection.

Table 1. The normalization of search volume in social media.

Input Key Terms			Google Search		Twitter	
1st	2st	3st	Normalization (N_i)			
			1st + 2st	1st + 2st + 3st	1st + 2st	1st + 2st + 3st
Quality			0.71	0.76	1	–
Technological capability			0	0.01	0	–
Pollution control	LED	One Belt and One Road	0	0.06	0	–
Environmental management			0.01	0.08	0	–
Green products			0.28	0.01	0	–
Green competencies			0	0.08	0	–

–: None.

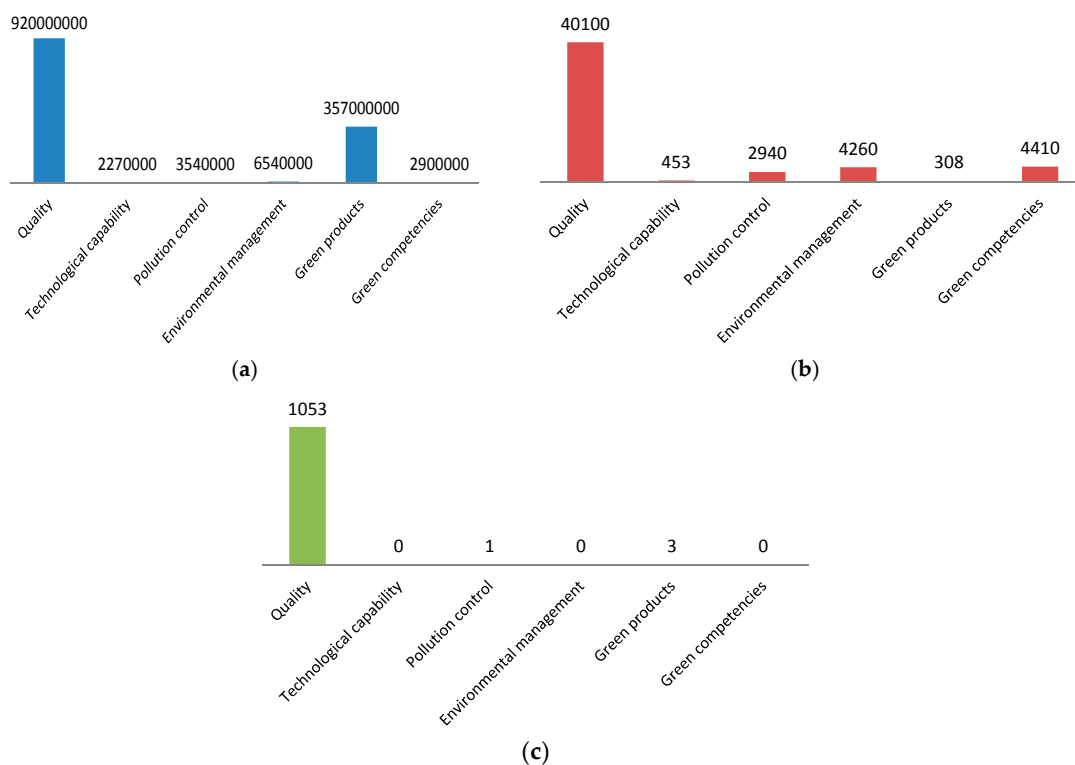


Figure 3. The search volume in social media. (a) The volume of key terms (1st + 2st) in google search; (b) The volume of all key terms (1st + 2st + 3st) in google search; (c) The volume of key terms (1st + 2st) in twitter.

Step 2 Computing the fuzzy weights with social media information

In this study, we adopted the linguistic terms which might be vague to determine exact value. The linguistic terms could transfer to triangular fuzzy numbers (TFNs). Table 2 shows the linguistic terms and fuzzy numbers of the importance weighting rating and are expressed as a linguistic variable by experts. The arithmetic equation is shown as follows:

$$W_i = \frac{1}{g} \sum_{k=1}^g \tilde{E}_k, i = 1, 2, \dots, n, \tag{2}$$

where the \tilde{E}_k ($k = 1, 2, \dots, g$) denotes the linguistic variable by the k th expert. Let $\tilde{E}_1 = (e_{11}, e_{12}, e_{13})$ and $\tilde{E}_2 = (e_{21}, e_{22}, e_{23})$ are TFNs. The fuzzy addition and division can be formulated as following:

$$\tilde{E}_1 + \tilde{E}_2 = (e_{11} + e_{21}, e_{12} + e_{22}, e_{13} + e_{23}) \tag{3}$$

$$\tilde{E}_1 / \tilde{E}_2 = (e_{11}/e_{23}, e_{12}/e_{22}, e_{13}/e_{21}) \forall e_{21}, e_{22}, e_{23} \neq 0. \tag{4}$$

Then, aggregated fuzzy weights with social media can be calculated by fuzzy arithmetic in Table 3. For example, the aggregated fuzzy weights are calculated by the linguistic variables from experts, which the experts 1 to 3 give as “M”, “MI”, and “I”, respectively. Based on Equation (2), the aggregated fuzzy weights (0.500, 0.700, 0.867) can be calculated. The aggregated fuzzy weights with social media in the Google search (1st + 2st) (0.355, 0.497, 0.615) is calculated by (0.500, 0.700, 0.867) × N_1 (0.71).

Table 2. Linguistic variables for green supplier’s importance weight.

Linguistic Variables	TFNs
Very important (VI)	(0.9, 1.0, 1.0)
Important (I)	(0.7, 0.9, 1.0)
Medium important (MI)	(0.5, 0.7, 0.9)
Medium (M)	(0.3, 0.5, 0.7)
Medium unimportant (MU)	(0.1, 0.3, 0.5)
Unimportant (U)	(0.0, 0.1, 0.3)
Very unimportant (VU)	(0.0, 0.0, 0.1)

Table 3. The fuzzy weights of the criteria and the aggregated fuzzy weights with social media information.

Criterion	Sub-Criterion	Aggregated Fuzzy Weights	Aggregated Fuzzy Weights with Social Media		
			Google Search (1st + 2st)	Google Search (1st + 2st + 3st)	Twitter (1st + 2st)
C ₁	C ₁₁	(0.500, 0.700, 0.867)	(0.355, 0.497, 0.615)	(0.380, 0.532, 0.659)	(0.500, 0.700, 0.867)
	C ₁₂	(0.000, 0.067, 0.233)	(0, 0.047, 0.165)	(0, 0.051, 0.177)	(0.000, 0.067, 0.233)
	C ₁₃	(0.700, 0.900, 1.000)	(0.497, 0.639, 0.71)	(0.532, 0.684, 0.760)	(0.700, 0.900, 1.000)
C ₂	C ₂₁	(0.233, 0.433, 0.633)	(0, 0, 0)	(0.002, 0.004, 0.006)	(0, 0, 0)
	C ₂₂	(0.700, 0.900, 1.000)	(0, 0, 0)	(0.007, 0.009, 0.010)	(0, 0, 0)
	C ₂₃	(0.433, 0.633, 0.800)	(0, 0, 0)	(0.004, 0.006, 0.008)	(0, 0, 0)
	C ₂₄	(0.133, 0.300, 0.500)	(0, 0, 0)	(0.001, 0.003, 0.005)	(0, 0, 0)
C ₃	C ₃₁	(0.700, 0.900, 1.000)	(0, 0, 0)	(0.042, 0.054, 0.060)	(0, 0, 0)
	C ₃₂	(0.433, 0.633, 0.800)	(0, 0, 0)	(0.026, 0.038, 0.048)	(0, 0, 0)
	C ₃₃	(0.233, 0.433, 0.633)	(0, 0, 0)	(0.014, 0.026, 0.038)	(0, 0, 0)
	C ₃₄	(0.033, 0.167, 0.367)	(0, 0, 0)	(0.002, 0.010, 0.022)	(0, 0, 0)
	C ₃₅	(0.633, 0.833, 0.967)	(0, 0, 0)	(0.038, 0.050, 0.058)	(0, 0, 0)
C ₄	C ₄₁	(0.133, 0.300, 0.500)	(0.001, 0.003, 0.005)	(0.011, 0.024, 0.040)	(0, 0, 0)
	C ₄₂	(0.767, 0.933, 1.000)	(0.007, 0.009, 0.01)	(0.061, 0.075, 0.080)	(0, 0, 0)
	C ₄₃	(0.100, 0.200, 0.367)	(0.001, 0.002, 0.003)	(0.008, 0.016, 0.029)	(0, 0, 0)
	C ₄₄	(0.433, 0.633, 0.800)	(0.004, 0.006, 0.008)	(0.035, 0.051, 0.064)	(0, 0, 0)
C ₅	C ₅₁	(0.633, 0.833, 0.967)	(0.177, 0.233, 0.270)	(0.006, 0.008, 0.010)	(0, 0, 0)
	C ₅₂	(0.767, 0.933, 1.000)	(0.214, 0.261, 0.28)	(0.008, 0.009, 0.010)	(0, 0, 0)
	C ₅₃	(0.767, 0.933, 1.000)	(0.214, 0.261, 0.28)	(0.008, 0.009, 0.010)	(0, 0, 0)
C ₆	C ₆₁	(0.033, 0.167, 0.367)	(0, 0, 0)	(0.003, 0.013, 0.029)	(0, 0, 0)
	C ₆₂	(0.100, 0.200, 0.367)	(0, 0, 0)	(0.008, 0.016, 0.029)	(0, 0, 0)
	C ₆₃	(0.133, 0.300, 0.500)	(0, 0, 0)	(0.011, 0.024, 0.040)	(0, 0, 0)
	C ₆₄	(0.833, 0.967, 1.000)	(0, 0, 0)	(0.067, 0.077, 0.080)	(0, 0, 0)

Step 3 Computing each criterion and the aggregated ratings for each green supplier

Table 4 shows the linguistic variables that can map onto TFNs for the green supplier criteria. In this study, seven scales are adopted for computing each criterion.

Table 5 shows the calculation results of green supplier’s criteria by fuzzy arithmetic as green supplier’s importance weight. These results can be calculated based on those TFNs that are determined

by three experts for evaluating green suppliers. For example, the aggregated fuzzy criterion is calculated by the linguistic variables from experts that experts 1 to 3 give as “MP”, “MG”, and “MG”, respectively. Hence, the aggregated ratings for GS_1 can be calculated as aggregated fuzzy weights.

Table 4. Linguistic variables for green supplier criteria rating.

Linguistic Variables	TFNs
Very good (VG)	(0.833, 1.000, 1.000)
Good (G)	(0.667, 0.833, 1.000)
Medium good (MG)	(0.500, 0.667, 0.833)
Medium (M)	(0.333, 0.500, 0.667)
Medium poor (MP)	(0.167, 0.333, 0.500)
Poor (P)	(0.000, 0.167, 0.333)
Very poor (VP)	(0.000, 0.000, 0.167)

Table 5. The experts’ assessment under each criterion and the aggregated ratings for each green supplier.

Criteria	GS_1	GS_2	GS_3	GS_4	
C_1	C_{11}	(0.389, 0.556, 0.722)	(0.611, 0.778, 0.889)	(0.222, 0.389, 0.556)	(0.444, 0.611, 0.778)
	C_{12}	(0.389, 0.556, 0.722)	(0.500, 0.667, 0.833)	(0.500, 0.667, 0.833)	(0.500, 0.667, 0.833)
	C_{13}	(0.444, 0.611, 0.778)	(0.667, 0.833, 0.944)	(0.389, 0.556, 0.722)	(0.611, 0.778, 0.944)
C_2	C_{21}	(0.333, 0.500, 0.667)	(0.722, 0.889, 1.000)	(0.500, 0.667, 0.833)	(0.722, 0.889, 1.000)
	C_{22}	(0.444, 0.611, 0.778)	(0.444, 0.611, 0.778)	(0.389, 0.556, 0.722)	(0.444, 0.611, 0.778)
	C_{23}	(0.778, 0.944, 1.000)	(0.333, 0.500, 0.667)	(0.444, 0.611, 0.778)	(0.333, 0.500, 0.667)
	C_{24}	(0.444, 0.611, 0.778)	(0.389, 0.556, 0.722)	(0.389, 0.556, 0.722)	(0.389, 0.556, 0.722)
C_3	C_{31}	(0.611, 0.778, 0.944)	(0.389, 0.556, 0.722)	(0.611, 0.778, 0.944)	(0.389, 0.556, 0.722)
	C_{32}	(0.333, 0.500, 0.667)	(0.389, 0.556, 0.722)	(0.333, 0.500, 0.667)	(0.389, 0.556, 0.722)
	C_{33}	(0.111, 0.278, 0.444)	(0.778, 0.944, 1.000)	(0.500, 0.667, 0.833)	(0.778, 0.944, 1.000)
	C_{34}	(0.000, 0.056, 0.222)	(0.444, 0.611, 0.778)	(0.667, 0.833, 0.944)	(0.444, 0.611, 0.778)
	C_{35}	(0.444, 0.611, 0.778)	(0.389, 0.556, 0.722)	(0.389, 0.556, 0.722)	(0.389, 0.556, 0.722)
C_4	C_{41}	(0.611, 0.778, 0.889)	(0.611, 0.778, 0.944)	(0.389, 0.556, 0.722)	(0.611, 0.778, 0.944)
	C_{42}	(0.500, 0.667, 0.833)	(0.389, 0.556, 0.722)	(0.111, 0.278, 0.444)	(0.389, 0.556, 0.722)
	C_{43}	(0.722, 0.889, 1.000)	(0.444, 0.611, 0.778)	(0.111, 0.278, 0.444)	(0.444, 0.611, 0.778)
	C_{44}	(0.778, 0.944, 1.000)	(0.333, 0.500, 0.667)	(0.611, 0.778, 0.944)	(0.333, 0.500, 0.667)
C_5	C_{51}	(0.389, 0.556, 0.722)	(0.500, 0.667, 0.833)	(0.111, 0.278, 0.444)	(0.611, 0.778, 0.944)
	C_{52}	(0.444, 0.611, 0.778)	(0.389, 0.556, 0.722)	(0.111, 0.278, 0.444)	(0.333, 0.500, 0.667)
	C_{53}	(0.111, 0.278, 0.444)	(0.778, 0.944, 1.000)	(0.611, 0.778, 0.944)	(0.000, 0.056, 0.222)
C_6	C_{61}	(0.444, 0.611, 0.778)	(0.667, 0.833, 0.944)	(0.222, 0.389, 0.556)	(0.444, 0.611, 0.778)
	C_{62}	(0.611, 0.778, 0.889)	(0.611, 0.778, 0.944)	(0.500, 0.667, 0.833)	(0.500, 0.667, 0.833)
	C_{63}	(0.500, 0.667, 0.833)	(0.389, 0.556, 0.722)	(0.389, 0.556, 0.722)	(0.611, 0.778, 0.944)
	C_{64}	(0.722, 0.889, 1.000)	(0.444, 0.611, 0.778)	(0.444, 0.611, 0.778)	(0.333, 0.500, 0.667)

Step 4 Aggregating the synthetic score using the proposed FWA with social media information method

Based on the collective rating values for four green suppliers in Table 5, the collective mapping fuzzy weight for each criterion in Table 3, and the procedure of our proposed FWA with social media information, the FWA performances of six criteria categories can be computed for four green suppliers in Table 6, and thus the membership function curves of the overall FWAs GS_1 , GS_2 , GS_3 , and GS_4 can thus be drawn, as shown in Figure 4.

Table 6. The comparison of FWA and FWA with social media information scores.

Suppliers	GS ₁	GS ₂	GS ₃	GS ₄
Traditional FWA	(0.473, 0.633, 0.777)	(0.489, 0.662, 0.810)	(0.370, 0.543, 0.715)	(0.413, 0.569, 0.734)
Google search (1st + 2st)	(0.377, 0.546, 0.714)	(0.606, 0.770, 0.887)	(0.306, 0.474, 0.652)	(0.438, 0.596, 0.769)
Google search (1st + 2st + 3st)	(0.456, 0.617, 0.770)	(0.585, 0.749, 0.872)	(0.340, 0.511, 0.685)	(0.503, 0.662, 0.822)
Twitter (1st + 2st)	(0.421, 0.586, 0.749)	(0.644, 0.803, 0.909)	(0.319, 0.490, 0.666)	(0.541, 0.703, 0.863)

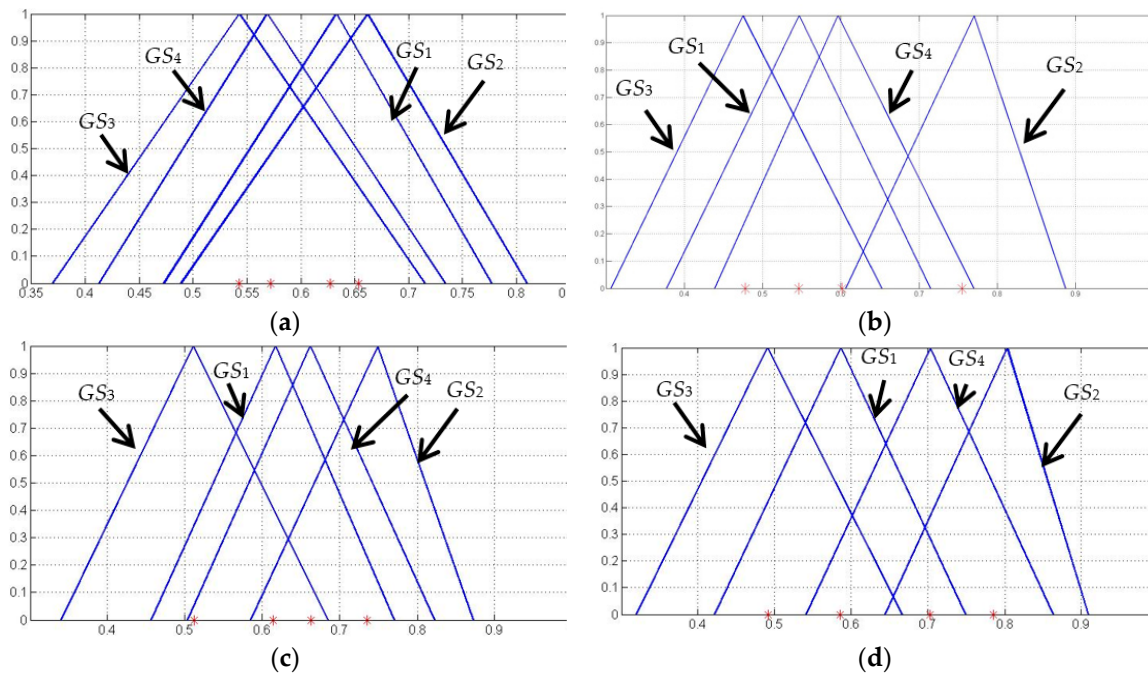


Figure 4. The membership functions of FWA with social media information scores of GS₁, GS₂, GS₃, and GS₄. (a) Traditional FWA; (b) Google search (1st + 2st); (c) Google search (1st + 2st + 3st); (d) Twitter (1st + 2st).

Step 5 Ranking the green supplier evaluation through the final synthetic scores

According to Figure 4 and Table 6, when applying the α -cut-based method [40], we can obtain $GS_2 \succ$ (superior to) $GS_1 \succ GS_4 \succ GS_3$ in traditional FWA and $GS_2 \succ GS_4 \succ GS_1 \succ GS_3$ in FWA with social media information. The social media main tuned the fuzzy weights in C_1 and C_5 . Public discussion was focus on “Quality” and “Green products” criteria in the LED industry. Based on the fuzzy weighted tuned, the supplier GS_4 should be superior to GS_1 . The evaluating results may provide the decision maker with useful and informative decision references.

This study develops a multi-criteria decision-making (MCDM) model to facilitate evaluation procedures in the LED green supply chain. In the evaluation of suppliers, a number of criteria can be quantified, while others are strictly qualitative. This study proposes an FWA with social media information to convert qualitative data into quantitative values via linguistic variables in order to facilitate the process of decision-making and consider the volume of discussion in social media information. The OBOR is also considered as a key input term. In the LED industry, manufacturers require the ability to select the best vendor from among thousands of potential suppliers. Thus, the ability to rapidly evaluate the capabilities of suppliers according to specific evaluation criteria is essential. The proposed FWA is an effective tool for the evaluation of suppliers, with the ability to streamline the decision-making process.

4. Conclusions and Future Research

Supplier evaluation is crucial for consumers in the LED industry. Previous studies have reported that the criteria used in the selection of suppliers could be extended to include green (environmental) criteria. In addition, the process of selecting suppliers tends to be incomplete, imprecise, and vague. This study uses fuzzy analysis with social media information to allow decision-makers to take full advantage of the information available to them and consider the social media information in fuzzy weights. The fact that fuzzy aggregation is able to handle linguistic as well as ordinary quantitative information enables users to deal with decision-making problems based on multiple criteria. Moreover, the social media information will actually influence the fuzzy weight of the expert, which lets the fuzzy weights be more objective. The final evaluation of green supplier selection is also changed in the LED industry because of the social media information. Based on the results of the proposed FWA model, we can observe that (1) the consumer's main concerns are the "Quality" and "Green products" in the LED industry, (2) the OBOR in the LED industry has no fervently discuss in Google search and Twitter, and (3) the FWA with social media information can objectively analyze the green supplier selection, which may be better than the traditional FWA.

Future researchers could apply this approach to other decision-making problems in manufacturing and other management applications, including material substitution selection, location selection, flexible manufacturing systems, and office layouts. Moreover, the D numbers or influential diagram could also be employed to proposed decision methods in further research.

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