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Abstract：Due to an increased awareness of ecological protection and resultant stringent legislations, business organizations are highly motivated to improve the sustainable performance of their supply chain in order to achieve sustainable development goals. The chemical industry is a high-risk, high-pollution, and high-efficiency industry, that would benefit from a systematic and sustainability focused evaluation system for supplier selection. Yet, to date, few studies have conducted the necessary in-depth analysis of the characteristics of this industry from the economic, social, and environmental perspectives. Despite the many methods and models that have been proposed to resolve the sustainable supplier selection (SSS) problem, no research has yet considered the different characteristics of each triple bottom line dimension. Accordingly, this paper addresses this problem by proposing a hybrid multi-method and multi-criteria decision-making framework for SSS in the chemical industry. Based on specific characteristics of the chemical industry, this study applies Fuzzy Grey Relational Analysis (FGRA), Failure Mode and Effects Analysis (FMEA), and cloud computing-entropy weight method (EWM) to analyze the economic, social, and environmental dimensions, respectively. Finally, this study integrates the evaluation results of the three dimensions using the Decision-making Trial and Evaluation Laboratory (DEMATEL). The proposed approach and decision-making model can help managers of sustainable supply chains in the chemical industry to choose more sustainable suppliers, respond to market demands quickly, and maintain high competitiveness in the market. An illustrative application of the proposed framework and model is undertaken in one of the biggest Chinese petrochemical companies to verify its practicality and reliability.

Keyword: Supplier selection; Sustainable supply chain; Chemical industry; Dimensional analysis

1. Introduction

Sustainability is the ability of an organization to make real-time decisions without any disadvantageous impact on the future condition of the environment, society, and business stability (Tirkolaee et al., 2020). As global awareness of the environment and sustainability continues to rise, governments become more focused and communities become more knowledgeable (Kannan, 2018). Pressure from regulations and policies, consumers, non-governmental organizations, and market competitors have all led firms to apply the concept of having sustainable supply chains (SSCs) (Lin et al., 2015). Therefore, the incorporation of ecological, economic, and societal aspects to ensure sustainable development is a foremost strategic task for business organizations in recent years (Benn, 2018; Rashidi & Cullinane, 2019).

The performance of partners influences the performance of downstream enterprises (Duman et al., 2017) as well as the production and operations performance of purchasers (Kaya & Yet, 2019). Suppliers play a vital role in implementing SSC initiatives and in achieving social, environmental and economic gains (Wu & Barnes, 2012; Shen et al., 2013). Hence, to improve business performance and competitive advantage, acquiring green and sustainable supplier selection (SSS) is the key decision in supply chains (Govindan et al., 2013). In practice, ineffective or inappropriate suppliers could result in some negative corporate social responsibility (CSR) and environmental issues in the supply chain. For example, the UK fashion brand Primark suffered manufacturing disruption and brand reputation damage because of its neglect of CSR and safety issues in the process of supply qualification and classification (Wu et al., 2020a).

Nowadays, the chemical industry’s position in the Chinese national economy is becoming more and more important and the industry can promote industrial development and provide many positions for employment. According to statistics from the China National Petroleum Corporation, China's consumption of polyethylene in

2019 is 32 million tons, accounting for one-third of world demand (Chou, 2020). However, as the production of most chemicals is highly hazardous and could potentially cause irreversible environmental damage and negatively affect the health of the public, safe and sustainable production is the primary dictum for the sustainable development of chemical companies. Additionally, the raw materials used in the chemical industry are characterized by diversity, considerable risk, and complicated operations (Yang et al., 2020). Moreover, there are various security risks in the whole manufacturing and transportation process. Without safe and sustainable supply chains, there would be huge irrecoverable losses. From 2012 to 2020, there have been many serious accidents at chemical plants around the world, resulting in hundreds of deaths and thousands of injuries.

For instance, on March 25, 2019, a chemical company in Shandong experienced an explosion and fire due to the excessive moisture content of the raw material, tin tetrachloride, and the solvent, xylene. Furthermore, on January 14, 2020, a large-scale explosion occurred in a chemical plant in Spain. The enterprise where the accident occurred was the only producer of ethylene oxide and ethylene glycol in Spain and Portugal. Consequently, the accident may increase the price of domestic chemical products such as ethylene oxide and ethylene glycol within a certain period. An analysis of the causes of the above accidents revealed that most of the raw materials or production equipment provided by the suppliers have quality problems.

Catastrophic chemical accidents, often with severe human casualties, result in adverse effects on sustainable development. Therefore, the selection of sustainable suppliers is not only important to meet the needs of the enterprise itself but also for the safety and sustainability of production in the chemical industry. However, to date, few studies have conducted the necessary in-depth analysis of the characteristics of the chemical industry from the economic, social, and environmental perspectives. Although many methods and models have been proposed to resolve the SSS problem, no research has yet considered the different characteristics of each triple bottom line (TBL) dimension.

In the chemical industry, each of the TBL dimensions has distinctive characteristics, namely:

(1) Economic: there are relatively small cost/price differences due to the capital-intensive nature of most chemical production processes.
(2) Social: there is greater uncertainty in decision-making due to the high-risk attributes of the chemical industry.
(3) Environmental: there is an imperative in the chemical industry for carbon footprint tracking that creates complex relationship between supply chain partners.

Accordingly, there is a need to deploy specific methods to analyze and evaluate each of the different TBL dimensions separately. Additionally, on completion, there is a need to integrate the results of the analysis of each of the different TBL dimension in order to identify the most appropriate suppliers.

Thus, the principal research question for this study is:

> *"How can the most appropriate sustainable suppliers in the chemical industry be evaluated and identified in accordance with the triple bottom line principle?*

Additionally, given the distinctive characteristics of the different TBL dimensions in the chemical industry, there are two supplementary research questions:

- *How can suitable methods or sub-models be chosen and designed for each of the different TBL dimensions?*
- *How can the results of the analysis of each of the different TBL dimension, be integrated, efficiently and effectively?*

To address these questions, we propose an integrated decision-making approach for SSS in the chemical industry based on the TBL principle and using specific methods of analysis for each of the TBL dimensions.

Therefore, this research, firstly, plans to apply Fuzzy Grey Relational Analysis (FGRA) to perform simple but effective analyses of the economic dimension. Second, this research adopts Failure Mode and Effects Analysis (FMEA) to perform risk analysis in the social dimension. Furthermore, this research applies Techniques for Order Preferences by Similarity to Ideal Solution (TOPSIS) under Interval-valued Pythagorean Fuzzy Set Theory (IVPFST) to deal with uncertainty in this decision-making environment. Thirdly, this research uses cloud computing to track the carbon footprint while the Entropy Weighted Method (EWM) is used to eliminate human interference and deal with the complex relationships among environmental indicators. Finally, to apply the above evaluations on the TBL dimensions effectively, this research applies cloud Decision-making Trial and Evaluation Laboratory (DEMATEL) to assign appropriate weights to each dimension. By adopting the above methods effectively and smoothly, the framework and sub-models proposed can help decision-makers evaluate and identify the most appropriate sustainable suppliers in the chemical industry.

The rest of the paper is organized as follows. Section 2 reviews the extant research on SSC management, including criteria and methodologies for SSS. Section 3 introduces the proposed framework and sub-models for SSS in the chemical industry. Section 4 presents an illustrative application of the proposed approach. Section 5 performs sensitivity and comparative analysis. Section 6 discusses the results and Section 7 presents managerial implications. Finally, Section 8 closes the paper with concluding remarks and suggestions for future research.

2. Literature review

2.1 Sustainable supply chain in the chemical industry

Most of the existing research on sustainability in the chemical industry have focused on industrial processes and technologies, such as the impact of raw materials on sustainability (Guo et al., 2019) and the transformation of sustainable operations

(Brömer et al., 2019). Nikolopoulou & Ierapetritou (2012) studied literature on sustainable chemical processes and supply chain design, focusing on energy efficiency, water and waste management, and environmentally SSCs. They summarized the future opportunities within a multi-objective optimization framework from a TBL perspective. Moreover, Rajeev et al. (2019) identified the strengths and weaknesses of the existing literature on various issues, opportunities, and challenges of managerial studies on SSCs in chemical industries. They suggested that the studies on the impact of sustainability practices in various functional domains need to be extended. These researchers acknowledge that SSS is highly necessary for the chemical industry.

However, there is little research on the selection of sustainable supply partners in the chemical industry. Yildiz & Yayla (2015) concluded from 91 studies on supplier selection problems between 2001 and 2014 that the major industries involved in supplier selection are electrical-electronics, automotive, furniture, white goods, agriculture-construction, transportation-logistics, and the textile industry. In recent years, apart from the above industries, research on supplier selection includes construction (Wang et al., 2017), printing (Diouf & Kwak, 2018), and plastic packaging industries (Zarbakhshnia & Jaghdani, 2018). Only Tong et al. (2019; 2020) proposed applicable methodologies to evaluate and select equipment maintenance suppliers in the chemical and petrochemical industry.

Therefore, we conclude that previous research paid significant attention to general manufacturing industries, while overlooking the chemical industry. In comparison to other industries, the costs for environmental protection in chemical industry are among the highest, and chemical enterprises are increasingly being held responsible for the environmental misconduct of their suppliers (Fick et al., 2009). Moreover, responsible social behavior is of utmost importance for chemical firms to avoid fatal incidents, similar to those that occurred in the 1980s and 1990s (Christmann, 2000) because stakeholders closely scrutinize the industry's high profitability and operations. According to the Classification, Labelling and Packaging Regulation (CLP) in the EU

(Gordalla et al., 2013), chemical hazardous materials are usually characterized as inflammable, explosive, toxic, corrosive, and carcinogenic. Once accidents happen in a chemical company, they can lead to irreparable damage and fatalities. Therefore, in the chemical industry, it is highly necessary to select the most appropriate sustainable suppliers.

2.2 Criteria for sustainable supplier selection

Pioneering research from Dickson (1966), identified 23 economic criteria for supplier selection (including product quality, on-time delivery, and performance history of suppliers). More recently, Ho et al. (2010) found the most popular supplier selection criteria are quality, delivery, and price. Furthermore, Chang et al. (2011) studied the top ten criteria most prevalent in the literature, including cost, delivery, reliability, flexibility, quality, and capability of relevant facilities. Buyukozkan & Cifci (2011) suggested that an effective supplier evaluation process should consider a wide range of factors such as quality, technology, and capacity, amongst others. On the one hand, a high-quality product can prevent economic, ecological, and social losses, and supplier selection is an essential element to build strong SSC management (Chen et al., 2019). On the other hand, considering the quantity and quality loss of goods during transportation (Tang et al., 2019), the supplier may intentionally underload the goods during the loading process. Therefore, to evaluate suppliers in the economic dimension, indicators such as quality, cost / price, delivery time, and transit loss are essential.

Over the past few decades, environmental issues have received widespread attention from the government, the public, and researchers (Buyukozkan & Cifci, 2012). Affected by this long-term "green" idea, many supplier selection models have integrated environmental indicators (Azadnia et al., 2013). According to Govindan et al., (2015), the most widely adopted criterion for green supplier evaluation and selection is an environmental management system. To this end, Buyukozkan & Cifci (2011) found that most of the companies ask their suppliers to implement ISO 14001, as this has become the most prevalent environmental management system. The use of environmentally friendly material and technology is the major criterion in green supplier selection (Govindan et al., 2013). Some studies are also based on potential drivers like green supply chain management capabilities, strategic level of the purchasing department, the level of environmental commitment, the degree of green supplier assessment, and the degree of green supplier collaboration (Junior & Filho, 2010). In addition to the above criteria, the models in recent studies also consider carbon emissions. Yu et al., (2018) suggested an eco-friendly supplier selection incentivized framework based on greenhouse gas emissions, which encourages the stakeholders within the supply chain to take the initiative to make eco-friendly decisions.

Barkemeyer et al. (2014) argue that the social dimension of SSS was neglected in management and business research for a long time. However, in recent years, it has received more attention and is increasingly being incorporated into supplier selection models (Amindoust et al., 2012; Azadnia et al., 2013). Accordingly, Bai & Sarkis (2010) categorized social metrics for supplier selection decisions as either: (1) Internal social criteria including employment practices and safety factors, or (2) External social criteria including local communities' influence, contractual stakeholders' influence, and other stakeholders' influence. Govindan et al. (2013) used employment practices, health and safety, local community influences, and contractual stakeholders' influence as the social criteria to select appropriate suppliers. Costa & Menichini (2013) found that the corporate social responsibility dimension has received less attentions than environmental dimension. Until 2017, Nematollahi et al., (2017) focused on CSR impacts and applicability to supply chain management. They recommended that firms should pay more attention to social responsibilities and investment to get more CSR beneficences.

In summary, from the above reviews, we can see that criteria for each of the three different TBL dimensions have distinctive characteristics. At the same time, each decision-making method has its own emphasis and advantages. There is no single method or model that can solve the complex SSS problem, comprehensively and systematically. In other words, we need to select specific methods suitable for the different TBL dimensions according to the distinct characteristics and actual conditions of each dimension in the chemical industry.

2.3 Decision-making methods/models for sustainable supplier selection

SSS is one of the key strategic decisions to manage sustainable development (Amindoust et al., 2012). When evaluating multiple suppliers, Sarkis & Dhavale (2015) pointed out that supplier selection is crucial for SSC partnership development and noted that complexities occur. Previously, many scholars have adopted different models and methods for SSS in different industries. Fallahpour et al., (2017) address the problem of SSS through the use of a questionnaire survey and obtained supportive results using a case study. The sustainable supplier evaluation framework of the above researchers is based on the qualitative evaluation inputs of decision-makers, which are often imprecise and vague (Azadnia et al., 2013).

Many researchers use fuzzy set theory to make up for the deficiency of qualitative evaluation. Bai & Sarkis (2010) advanced the use of the grey system and the rough set theory to analyze supplier selection decisions by incorporating sustainability factors in their models. Buyukozkan & Cifci (2012) proposed a hybrid multi-criteria decision making (MCDM) model to evaluate green suppliers by combining fuzzy DEMATEL, ANP and TOPSIS. Govindan et al. (2013) presented a model with fuzzy TOPSIS to evaluate the performance of a supplier against the requirements of sustainability criteria. They suggested that companies should assess and rank their supply chain activities in order to implement sustainability opportunities. In short, ANP, TOPSIS, DEMATEL and other methods combined with fuzzy set theory have been widely used in supplier selection.

However, You et al. (2015) found that in the process of selecting suppliers, decision-makers are often uncertain about their preferences because of time constraints, and the lack of experience and data. Moreover, evaluation information is often imprecise, uncertain, and incomplete. In this case, IVPFST can effectively capture uncertain information (Rahman et al., 2017). It has great ability to address strong fuzziness, ambiguity, and inexactness during the decision-making process. Therefore, when the decision-making conditions are completely unknown, IVPFST is applicable to capture uncertain information in SSS.

At the same time, safety in both production and delivery are essential to the chemical industry. From the perspective of a chemical manufacturer, process engineers must be able to predict possible problems or failures during the whole production process. Evaluating the risks associated with alternative suppliers in the social dimension can reduce the frequency of supply chain disruption and help maintain both good CSR and production safety (Lo et al., 2020). FMEA is one of the most commonly used methods for identifying critical failure modes. It can identify possible failure modes and evaluate their subsequent effects on the performance system (Bozdag et al., 2015). However, in many practical situations, the use of FMEA involves uncertain and incomplete assessments and decision-makers cannot easily evaluate alternatives using exact numerical values (Foroozesh et al., 2017).

Moreover, with the development of industrial technology, Sampath Kumar et al. (2019) defined the concept of Industry 4.0 (I4.0) from an ontological point of view. The architecture based on big data, cloud computing and Internet of Things technology can not only save internal labor costs and reduce pollutant emissions for manufacturing enterprises, but also effectively meet customers' personalized, customized and diversified requirements externally, thus improving customer dependence (Tang, 2004). Therefore, I4.0 requires enterprises to build platforms with upstream suppliers to achieve more efficient data sharing.

Based on machine learning theory, some research created a cloud manufacturing platform connecting numerous customers and suppliers. Simeone et al., (2020) adopted a deep neural network for automatic learning of optimal solutions based both on customers' past experiences. Olszewska & Strain (2020) use Naive Bayesian network, which requires only a small amount of data to train the system, to cope with fashion trends and seasonal shifts. Combining ensemble learning technology and fuzzy set theory, Wu et al. (2020b) proposes a partner classification model. In addition, Singh et al. (2018) proposed a cloud computing based big data framework to select suppliers in the beef supply chain for low carbon emission. Based on the major advantages of cloud computing technology, including cost reduction, faster deployment of computer resources, and improved information visibility, the above research results show that supplier evaluation systems based on the cloud model are effective.

More specifically, as many types and copious quantities of pollutants can be emitted during chemical production processes, carbon management and green gas emission management are key criteria in SSS. Therefore, considering the carbon footprint of suppliers is of great significance to the sustainable development of the chemical industry. In existing research, carbon emission has been traditionally addressed in three ways namely, strict emission caps, carbon taxes, and cap-and-trade (Lamba et al., 2019). However, there is a possibility of missing data in the tracking of a carbon footprint. A private cloud that conveniently tracks the CO_2 produced by raw materials from production to distribution, provides better control over the cloud infrastructure (Marston et al., 2011). However, few researchers use it to efficiently track the carbon footprint of suppliers by cloud computing.

2.4 Research gaps

The above literature review highlights the rapid increase in attention given to SSS in recent years. Based on this, we summarize and identify the following four interesting and important research gaps.

(1) Although various researchers have proposed different models/methods for SSS, few of them focus on the chemical industry. The selection of sustainable suppliers in the chemical industry represents one of the current research gaps, and associated studies are urgently needed.

(2) When analyzing the SSS problem, most of the current research is based on the TBL dimensions. However, as the criteria in the different TBL dimensions have distinctive characteristics, it is necessary to match these characteristics with specific methods or models to ensure high efficiency and effectiveness in decision-making. However, to date, few researchers have considered the different characteristics of each TBL dimension, separately and systematically.

(3) Safety and risk management in both production and delivery are essential to the chemical industry. On the one hand, whilst FMEA has been used by some researchers to identify the risks of suppliers under evaluation criteria, there are few examples of its application in the chemical industry. On the other hand, the use of FMEA cannot easily evaluate alternatives using exact numerical values. This shortcoming can be compensated by IVPFST, which can enable uncertain information to be captured and consider different opinions of multiple decision-makers within a group decision-making process. However, few studies evaluate potential suppliers combining both FMEA and IVPFST according to the characteristics of the social dimension.

(4) It is completely necessary to consider the carbon footprint of suppliers in the chemical industry. Whilst research on carbon footprint tracking is based on strict emission caps, carbon taxes, and cap-and-trade, existing research can be further extended by using cloud computing to efficiently track the carbon footprint of potential suppliers.

This paper aims to address these research gaps and proposes a novel integrated approach for SSS in the chemical industry.

3. An integrated sustainable supplier selection approach in the chemical industry

This section proposes an integrated SSS approach for the chemical industry (shown in Figure 1). In the proposed framework, appropriate decision-making methods have been integrated to analyze the three TBL dimensions, respectively. The main reason for the adoption of different decision-making methods for each of the dimensions is that, in general, the selection of the evaluation method is best determined by the characteristics of the problem, the researchers, and the research objectives (Mishra et al., 2002). Accordingly, a separate evaluation model/method is selected for each dimension based on the characteristics and practicalities of each dimension. This, not only makes the proposed decision-making approach for SSS more practicable for use in this industry but also more objective as it enables the overall evaluation results to be displayed quantitatively. Hence, this study plans to take advantage of most appropriate method to evaluate the performance of potential sustainable suppliers in each of TBL dimensions.

[Insert Figure 1 about here.]

Firstly, to evaluate the economic dimension of potential suppliers, this research will use triangular fuzzy numbers (TFN) combined with a grey relational degree method (GRA). GRA has proven to be a simple but accurate ranking scheme to prioritize the order of grey relationships amongst dependent and independent selection criteria (Sallehuddin et al., 2008). However, Banaeian et al. (2018) found that Fuzzy GRA (FGRA) requires less computational complexity to generate the same results. FGRA can be used to manage both incomplete information and problem/system ambiguities, which is often the case when dealing with subjective data or insufficient/vague information. Therefore, FGRA is deemed most suitable for economic criteria dimension evaluation.

Second, when considering the social dimension, it is worth noting that production in chemical plants has the characteristics of high danger and large social impact in accidents. Therefore, petrochemical facilities and plants require essential ongoing maintenance to ensure high levels of reliability and safety (Wang & Liu, 2012). Undertaking a social risk assessment not only enhances production safety but also prevents occupational accidents and diseases (Goerlandt et al., 2017). FMEA is an effective risk analysis method for high-risk links (Kales, 1998). However, FMEA often encounters difficulties in dealing with the interrelationships between various failure modes with uncertainty and inaccurate information (Franceschini & Galetto, 2010). This shortcoming can be compensated by IVPFST, which can enable uncertainty to be captured effectively and consider different opinions of multiple decision-makers. More specifically, the application of IVPFST also solve the potential problem that the sum of affiliation and non-affiliation degrees is greater than one and the sum of their squares is less than one (Yager, 2013). Therefore, FMEA and IVPFST will be integrated to evaluate and rank potential suppliers with regard to the social dimension.

Third, since the production of CO_2 is essential to production in the chemical industry (Chen et al., 2019), the CO_2 emissions of upstream suppliers have a crucial impact on a firm’s environmental performance. Currently, in terms of sectoral CO_2 emission accounting and emission reduction, studies to date have considered on the electricity (Chen et al., 2016), iron and steel (An et al., 2018), and transportation sectors (Selvakkumaran & Limmeechokchai, 2015). The chemical industry seemingly lacks such related studies (Broeren et al., 2014), perhaps due to its numerous products and complex production processes, which make it a complicated system to analyze and one difficult to conduct comprehensive accounting within (Zhu et al., 2010). Additionally, poor data availability in the chemical industry has increased these difficulties (Griffin et al., 2018). Therefore, it is necessary to use a more suitable methodology to measure the CO_2 emissions of potential suppliers in the chemical industry. Process analyses are used to study the carbon footprint and to help enterprises calculate the CO_2 emissions generated in their own production process (Zhang et al., 2019). After uploading relevant production data from upstream suppliers, the suppliers' CO_2 emissions can be obtained through cloud computing. Then, the entropy weight coefficient method is used to deal with the complex interrelationships between environmental criteria and to determine the indicator weights (Isik, 2009). This will therefore be used to consider the environmental dimension of SSS.

Fourth, based on the respective evaluations of each dimension, this research proposes the application of both DEMATEL and cloud method to integrate the outputs of the previous three sub-steps. There are three motivations for combining DEMATEL and the cloud model together. (1) There is mutual influence between different dimensions. The influence between dimensions is not a simple relationship of an opposite number. The DEMATEL method can transform the relationship between elements and causal dimension from a complex system into an understandable structural model (Chang et al., 2011). However, the DEMATEL method cannot consider ambiguity and randomness (Xie et al., 2018). (2) The cloud model can describe the fuzziness and randomness of linguistic terms. It converts the evaluation information of decision-makers into a floating cloud, which can express the uncertainty of linguistic values more effectively (Wang & Liu, 2012). (3) When the DEMATEL method analyzes the relationship between dimensions, the elimination of a connection will cause some of the information to be lost during analysis (Kadoić et al., 2018). Fortunately, the cloud model can effectively express the uncertainty of linguistic values and the relationship information between dimensions (Wang & Liu, 2012), while avoiding the loss of information in the process of information aggregation. In short, the shortcomings of one method can be compensated by another method. Based on the cloud model, DEMATEL can improve decision-making effectiveness in complex situations, and make the criteria weights more reasonable and objective.

Table 1 briefly summarizes the methods and the reasons for their selection in the proposed approach.

[Insert Table 1 about here.]

3.1 Establishment of the expert group and customized criteria system

The application of the proposed model, as shown in Figure 1, depends on the appointment of a decision-making group, composed of relevant experts. Based on the TBL perspective, relevant criteria for SSS in the chemical industry were identified and selected by reviewing relevant literature based and conducting interviews with industrial experts. As Genovese et al., (2014) note, there is no single "criteria set" that fits all industries. In this study, we made use of a structured questionnaire filled out by experts to approve and select the relevant criteria based upon those suggested by the literature. After determining the criteria based on the industry, the next step was to conduct the three-dimensional analysis.

3.2 The three TBL dimensions of sustainable supplier selection

Following the proposed framework shown in Figure 1, the first step is to evaluate the criteria of the three TBL dimensions, respectively. It involves following three sub-steps.

3.2.1 Economic dimension evaluation

Banaeian et al. (2018) has shown Fuzzy GRA gets a better time complexity compared to Fuzzy TOPSIS and Fuzzy VIKOR and generates the results in a smaller number of steps and operations. Thus, this research follows the methodology of Banaeian et al. (2018) to evaluate and rank the potential suppliers in terms of economic criteria. The main steps are:

Step 1: Identify the appropriate linguistic variables

Step 2: Construct the aggregated fuzzy matrices

Step 3: Deblur and rank alternative suppliers in the economic dimension

A defuzzification formula was applied to $\tilde{w}_j$, then the grey relational grade γ_i was estimated by the relation

$$\gamma_i = \sum_{j=1}^{n} w_j \xi_{ij},\ i = 1,\ldots, m \tag{1}$$

where $\tilde{w}_j$ is the weight of j^{th} criterion, and $\sum_{j=1}^{n} w_j = 1$; ξ_{ij} is the grey relational coefficient.

The alternatives can now be ranked in accordance with the value of grey relational grade. The bigger the value, the better the alternative suppliers.

3.2.2 Social dimension evaluation

(1) Social dimension risk assessment

For the social dimension, this research evaluates the RPN (Risk Priority Number) risk of the evaluation criteria based on the evaluation gradients in Table 2 and obtained the risk appetite of decision-making experts for potential suppliers. Then the RPN value is converted into a seven-level Pythagorean fuzzy set, as shown in Table 3.

[Insert Tables 2 and 3 about here.]

(2) Evaluation of social dimension

Then, TOPSIS is used to defuzzify the Pythagoras fuzzy set and to calculate the weights to rank the alternative suppliers. Suppose that an MCDM problem has *m* alternatives $A = \{A_1, A_2,\ldots, A_m\}$, and *n* evaluation criteria $C = \{C_1, C_2,\ldots, C_n\}$. Each alternative evaluated by a decision-maker with respect to *n* criteria forms a decision-making matrix denoted by $D = (p_{ij})_{m \times n}$. Let $W = \{w_1, w_2,\ldots, w_n\}$ be the relative weight vector of the evaluation criteria. Then the main sub-steps of the SSS sub-model in the social dimension can be described as following:

Step 1: Determining Pythagoras' positive and negative ideal interval values.

$$p^{+} = (p_1^{+}, p_2^{+},\ldots,p_n^{+}) \tag{2}$$

$$p^{-} = (p_1^{-}, p_2^{-},\ldots,p_n^{-}) \tag{3}$$

$$p_j^+ = \max_i (p_{ij}) \tag{4}$$

$$p_j^- = \min_i (p_{ij}) \tag{5}$$

Step 2: Since the indicator weight is completely unknown, based on the close coefficient formula:

$$c_{ij} = \frac{d(p_{ij}, p_j^-)}{d(p_{ij}, p_j^-) + d(p_{ij}, p_j^+)} \tag{6}$$

we could get the index weight

$$w_j = \frac{c_j}{\sum_{j=1}^{n} c_j} = \frac{\sum_{i=1}^{m} c_{ij}}{\sum_{j=1}^{n} \sum_{i=1}^{m} c_{ij}}, \ j = 1, 2, \ldots, n \tag{7}$$

Step 3: Calculate the weighted distance between the evaluation value of each candidate supplier and the positive and negative ideal solutions.

$$d_i^+ = \sum_{j=1}^{n} w_j d(p_{ij}, p_j^+), \ i = 1, 2, \ldots, m \tag{8}$$

$$d_i^- = \sum_{j=1}^{n} w_j d(p_{ij}, p_j^-), \ i = 1, 2, \ldots, m \tag{9}$$

Step 4: Calculate the relative closeness coefficient of each candidate supplier, and then sort them according to the relative closeness of the candidate suppliers. The greater the relative closeness, the better the potential suppliers.

$$C_i = \frac{d_i^-}{d_i^- + d_i^+}, \ i = 1, 2, \ldots, m \tag{10}$$

3.2.3 Environmental dimension evaluation

(1) Carbon footprint tracking

The CO_2 emissions of the chemical industry come mainly from six sources, including fuel combustion emissions, fossil feedstock-related emissions, the indirect emissions generated by using electricity and heat, process emissions produced by carbonate and the reuse during the production of some chemicals (Chen et al., 2019). Thus, accounting for CO_2 emissions in the chemical industry should reflect these parts directly or indirectly (Chen et al., 2019). Cloud computing that has been used for quite a while in various sectors like automobiles, banks, healthcare, retail, logistics and education, can collect the relevant data easier and quicker (Al-Hudhaif & Alkubeyyer, 2011). In this study, companies can use a private cloud with upstream suppliers. The potential suppliers will have an account in the private cloud and input the required data shown in Figure 2. The information includes the power, heat, calcium carbonate, and its emission factor and purity that is used in production (Chen et al., 2019). Therefore, the total CO_2 emissions of one ton of products produced during the chemical production process of this enterprise can be calculated as:

$$E_{CO_2} = E_{CO_2}^{p-elec} + E_{CO_2}^{p-heat} + E_{CO_2}^{CaCO_3} \tag{11}$$

While

$$E_{CO_2}^{p-elec} = AD_{elec} \times EF_{elec} \tag{12}$$

$$E_{CO_2}^{p-heat} = AD_{heat} \times EF_{heat} \tag{13}$$

$$E_{CO_2}^{CaCO_3} = AD_{CaCO_3} \times EF_{CaCO_3} \times PUR_{CaCO_3} \tag{14}$$

$E_{CO_2}^{p-elec}$ is CO_2 emissions from net purchased electricity consumption, AD_{elec} is net purchased electricity consumption, and EF_{elec} is CO_2 emission factors for electricity supply.

$E_{CO_2}^{p-heat}$ is CO_2 emissions from net purchased heat consumption, AD_{heat} is net purchased heat consumption, and EF_{heat} is CO_2 emission factors for heat supply.

$E_{CO_2}^{CaCO_3}$ is CO_2 emissions from $CaCO_3$, AD_{CaCO_3} is $CaCO_3$ inputs, EF_{CaCO_3} is CO_2 emission factors for $CaCO_3$, and PUR_{CaCO_3} is the purity of $CaCO_3$.

[Insert Figure 2 about here.]

(2) The entropy value and objective weight of the evaluation attribute

The EWM is then used to obtain the objective weights of criteria. The following three steps are required:

Step 1: Standardized evaluation matrix**,** x_{ij} is the j^{th} criteria's value in i^{th} supplier.

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (15)$$

Step2：Calculation of the entropy value of evaluation criteria.

$$H_j = -k\sum_{i=1}^{m} p_{ij}\ln(p_{ij}) = -\frac{1}{\ln(m)}\sum_{i=1}^{m} p_{ij}\ln(p_{ij}),\ j = 1, 2, \ldots, n \quad (16)$$

Step 3: Calculation of the objective weights of criteria *j*.

$$w_j = \frac{1 - H_j}{n - \sum_{j=1}^{n} Hj},\ j = 1, 2, \ldots, n \quad (17)$$

Finally, the ranking of sustainable suppliers in the environmental dimension is determined by the decision-makers' evaluation and the carbon footprint.

3.3 Combination of the evaluations of TBL dimensions

After determining the rankings of potential suppliers in the above three dimensions respectively, the final step is to assign weights and combine them reasonably and effectively. Based on the cloud model proposed by Wang & Liu (2012), this research constructs an improved DEMATEL method to transform the preferences of experts from qualitative evaluations to quantitative ones in a completely uncertain language environment. The proposed improved DEMATEL method can reduce the lack of information. The weights of each dimension are calculated by the influenced degree (q_i) of each dimension. The specific sub-steps are summarized as follows:

Step 1: Transform decision-making information. Convert the uncertain language value given by the decision-makers into the expression form of a comprehensive cloud ($\tilde{y} = (Ex, En, He)$).

Step 2: The method of generating floating clouds in cloud theory is used for the aggregation of attribute values, to generate the comprehensive value of each criteria of each supplier for each decision-maker.

Step 3: Determine the weights of decision-makers. The information uncertainty and the deviation degree of the decision-maker are used to determine the weight of the decision-maker. The smaller the uncertainty of the evaluation matrix given by the decision-makers, the more accurate the decision of the decision-maker should be.

Step 4: Calculate the Hamming distance between each supplier and the positive and negative ideals' evaluation cloud. Calculate the Hamming distance between each attribute's mutual influence intensity evaluation cloud and the positive and negative ideal evaluation cloud to obtain the intensity relationship matrix $(D = [d_{ij}^{*}]_{n \times n})$ between attributes.

In detail, when calculating the distance between the alternatives and the ideal point, there are several efficient methods, for instance, the Hausdorff distance, which measures the maximum mismatch between two-point sets (Olszewska & Wilson, 2012), and the Hamming distance. This research paper uses Hamming distance to calculate the distance as it satisfies the basic requirement of its decision-making. In addition, when we get the Hamming distance between the alternatives and the ideal point, we also get the number of replacements required for the alternative to be the ideal solution.

Step 5: Standardize the impact matrix in accordance with Eq. 17. Then the comprehensive influence matrix *Z* is formed by Eq. 18, to measure the direct and indirect influences of each attribute.

$$M = [m_{ij}]_{n \times n} = D \Big/ \max_{1 \le i \le n} \sum_{j=1}^{n} d_{ij} \tag{17}$$

$$Z = M(I - M)^{-1} = (z_{ij})_{n \times n} \tag{18}$$

Step 6: The elements in the matrix *Z* are added in columns to obtain the influence degree of the corresponding attribute as $q_i = \sum_{j=1}^{n} z_{ji}$. Therefore, the influence weights of each criteria are $l_i = q_i \Big/ \sum_{i=1}^{n} q_i$.

Finally, we obtain the weights of the three TBL dimensions and then combine the rankings of potential suppliers in each dimension, which were obtained in sub-section 3.2. Thereafter, we can obtain the final ranking of the potential sustainable suppliers.

4. Empirical illustration

In this section, the proposed approach was applied at one of the biggest Chinese petrochemical companies, Company F (a pseudonym). The purpose was to illustrate the feasibility and practicability of the proposed approach in real business practice.

Company F is a large-scale petrochemical enterprise specializing in the management of chemical products, investment in and development of petrochemical projects, and the repair and maintenance of petrochemical equipment. Paraxylene acid (PTA) is one of the main products of Company F. The component para-xylene (PX) is the main raw material of PTA. The production of PTA is completely dependent on the sustainable supply of PX. However, due to high-risk chemical raw materials (such as PX, H_2), there are high potential environmental pollution problems in the production of PTA. Moreover, in the production process of PTA, the purity of PX required is extremely high. If there is a problem, such as an accident, it can have a severe result, for instance, fire. Therefore, if the raw materials have quality problems, it will result in great losses in economic cost, time to recovery, and the reputation of Company F. Therefore, it is vital to select the most appropriate suppliers and build a long-term partnership with them. With these goals in mind, Company F requires an effective and efficient decision-making process and solution to determine the most appropriate sustainable suppliers.

According to the above decision-making requirements, the decision-making group identified six potential PX suppliers (S_1, S_2, S_3, S_4, S_5, and S_6). They are large core producers of PX at home and abroad, especially, S_1 and $S_{4,}$ who are the main suppliers to Company F. S_2 has a smaller market share. S_3 and S_5 are PX leading companies, of which S_3 has a higher output and a larger market share. S_6 belongs to an agent, a foreign trade enterprise, that purchases raw materials and sells them to Company F.

Following the findings of Rezaei et al. (2018), who pointed out that a decision-making team of between four and ten experts is needed to obtain reliable data in MCDM analysis, and considering the organizational structure of Company F, a decision-making team was created comprising five senior executives from different levels and different functional departments. Based on their practical experience and professional knowledge, they jointly evaluated potential suppliers in each of the different TBL dimensions. The systematic application process of the proposed integrated approach for SSS in the chemical industry is shown below.

4.1 Construction of the customized criteria system

A set of customized criteria were identified through extensive literature reviews and discussions within the decision-making team. In order to ensure that all of the chosen criteria were relevant for the company, a questionnaire was designed in which the experts were asked to provide their opinions on whether a criterion was relevant or not. In addition, the experts were asked to recommend any missing criteria not already considered. In this way, 13 evaluation criteria were finally selected and classified into one of the three TBL dimensions as shown in Table 4.

[Insert Table 4 about here.]

4.2 Evaluation of the three dimensions in relation to the SSS

In the economic dimension, the decision-making team evaluated the performance of each potential supplier against each criterion. The group then filled out the questionnaire and thereby expressed their collective opinions in linguistic terms (as shown in Table 5). Then, the linguistic variables were converted into triangular fuzzy numbers.

Following the methodology proposed in Section 3.2.1, TFN was used to calculate the relative importance of different criteria and so derive the alternative suppliers' ranking.

Based on Table 5, the weights for the economic criteria were: price (0.2618), quality (0.0476), prompt delivery rate (0.1679), transportation loss (0.3398), and supply capacity (0.1829). The sum of the criteria weights times the grey relational coefficient (ξ_{ij}) was used to derive the grey relational grade using Eq. (1). Based on the above inputs, the rankings of potential suppliers for Company F were obtained in the economic dimension, as shown in Table 6.

[Insert Tables 5 and 6 about here.]

In order to get the ranking of alternative suppliers in the social dimension, the RPN value of the supplier's risk assessment under the criterion needed to be calculated first (show in Table 7). Then, it was converted into the corresponding Pythagorean fuzzy number (shown in Table 3).

[Insert Table 7 about here.]

The next sub-step was to determine the interval value Pythagoras' positive and negative ideal matrix, and to calculate the distance between each evaluation value and the positive and negative ideal evaluation value by Eq. (4) and (5).

$$p^{+} = (([0.80,0.95],[0.00,0.15]), ([0.80,0.95],[0.00,0.15]), ([0.80,0.95],[0.00,0.15]))$$

$$p^{-} = (([0.45,0.55],[0.40,0.55]), ([0.45,0.55],[0.40,0.55]), ([0.20,0.30],[0.70,0.80]))$$

Thereafter, the close coefficient was calculated by Eq. (6). The completely unknown attribute weights were determined by Eq. (7). The weights of the criteria in the social dimension were: CSR (0.3362), Production safety (0.3362), Employee benefits (0.3276).

In sub-step 3, the weighted distance between the comprehensive evaluation value and the positive and negative ideal solutions was calculated by Eq. (8) and (9).

$$d^{+} = (0.4735, 0.2560, 0.1250, 0.0000, 0.2500, 0.0000)$$

$$d^{-} = (0.0000, 0.2174, 0.3485, 0.4735, 0.2235, 0.4735)$$

Finally, the relative closeness coefficient was calculated by Eq. (10), from which the alternative suppliers were sorted. The calculation results are shown in Table 8.

[Insert Table 8 about here.]

According to the background and strength of each potential supplier, the decision-making team calculated the fuzzy score of the suppliers (as shown in the Table 9). Since Company F did not yet track the carbon footprint, the decision-making group evaluated each supplier's carbon emissions based on their experience. As set out in Section 3.2.3, the EWM was applied to calculate the weight of evaluation attributes objectively. H_j of each criterion were: $H_j = (34.88,\ 33.19,\ 27.26,\ 30.07,\ 30.17)$

Combined with the evaluation scores of each supplier, the final ranking of the environment dimension was calculated (as shown in Table 10).

[Insert Tables 9 and 10 about here.]

4.3 Integration and normalization of the three TBL dimensions

The decision-making team evaluated the interrelationships among the three dimensions and determined the weight of each dimension through the DEMATEL method based on the cloud model. The evaluation information given by the three decision-makers using the linguistic language is shown in Table 11. The decision-making information was transformed according to Step 3 shown in sub-section 3.3, and the weights of decision-makers were determined as 0.3743, 0.2741 and 0.3516, respectively. The comprehensive cloud matrix shown in Table 12 was from the analysis of the experts' evaluation based on DEMATEL. Table 13 shows the comprehensive influence, matrix *Z*, formed by the direct and indirect influences of different dimensions.

[Insert Tables 11-14 about here.]

From the analytical results shown in Table 14, the environment dimension (0.4229) was found as the most important criterion, followed by the economic dimension (0.3934), and then the social dimension (0.1837). Combining the analysis results of Section 4.2 with the suppliers ranking in different dimensions, produced the final ranking of the alternatives in descending order as $S_4>S_3>S_6>S_5>S_1>S_2$ (see Figure 3).

[Insert Figure 3 about here.]

5. Sensitivity and comparative analysis

5.1 Sensitive analysis

Sensitivity analysis helps to evaluate the stability of the proposed approach. In this sub-section, a single method for each dimension was used to calculate the overall sustainable supplier evaluation dimension and criteria weights. Thus, we assessed the final ranking of the alternatives by using the analysis method in each dimension separately (see Table 15). This also helps to check the consistency in decision-making. From Table 15, the results of sensitivity analysis showed that S_4 is highly ranking among all alternatives whether FGRA, FMEA, and IVPFST or EWM is adopted (shown in Figure 4 in a more intuitive way). Yet, the results obtained using different methods are not completely consistent. For example, S_2 ranks second in the social dimension method, but it ranks the lowest in the economy, environment dimension method. Before TOPSIS analysis, the decision-maker's evaluation of the supplier was converted into an interval Pythagorean fuzzy set for processing, that did not consider the interrelationship between the evaluation criteria, so that the result would be different. Coincidentally, the supplier ranking calculated by the EWM is consistent with the proposed approach. However, the premise of using the EWM is that the evaluation criteria are in the same dimension, which is obviously inconsistent with the TBL decision-making environment. In short, each dimension is analyzed separately and then summarized, thus the proposed approach not only considers the characteristics of each dimension of the chemical industry but also making the results more comprehensive.

[Insert Table 15 and Figure 4 about here.]

Furthermore, this sub-section changed the weights of each dimension to verify the robustness of the proposed sub-models. If we had not invited experts with an industry background to evaluate the dimensions but had averaged or arbitrarily assigned weights (simulated weights W_n) to different dimensions (Table 16), the changing in rankings would not be able to cannot guarantee the most sustainable supplier would be identified all the time.

[Insert Table 16 about here.]

By combining the weights of three TBL dimension in different scenarios in Table 16 with the dimensional rankings shown in Tables 7, 9 and 11, we obtained comprehensive supplier rankings in different scenarios (shown in Figure 5). First, if the weights were evenly distributed ($W_{eco} = W_{soc} = W_{env} = 1/3$), the rankings of S_3 and S_6 were swapped. Second, when the economic weight increased to a certain value, the positions of S_1, S_3, and S_5 changed. In detail, S_1 changed from the 5th to the 3rd, and both S_3 and S_5 dropped by one. The same happened to social and environment: when the social weight increased to a certain value, S_1 and S_2, S_4 and S_6 exchanged rankings; when the environmental weight increased and the economic weight decreased by a certain value, the rankings of S_5 and S_6 were exchanged. In summary, as the distribution weight of dimension changed, the rankings of suppliers also changed. So, if the weights cannot be reasonably allocated according to the characteristics of the chemical industry, the preliminary evaluation work will become meaningless and will affect lot-sizing. Therefore, the cloud model-based DEMATEL sub-model proposed in this study is reasonable and necessary. The weights obtained conformed to the industry background without distortion would help decision-makers identify the most appropriate sustainable suppliers.

[Insert Figure 5 about here.]

5.2 Comparative analysis

In order to validate of the proposed framework and decision-making model, this sub-section used the GRA and fuzzy-TOPSIS (FTOPSIS) for SSS while assuming the weights of each criterion to be equal (W_i=1/13). First of all, according to Eq. (1), the sum of criteria weights times grey relational coefficient (ξ_{ij}) derived the grey relational grade (shown in the second column of Table 17). Then, according to Banaeian et al. (2018)'s research, the evaluation information was transformed into a standard matrix. The positive ideal solution and the negative ideal solution for alternative suppliers were

$$d_i^- = \begin{bmatrix} (0.001,0.018,0.027),(0.018,0.028,0.041),(0.005,0.014,0.020), \\ (0.007,0.014,0.022),(0.004,0.010,0.019),(0.000,0.011,0.033), \\ (0.000,0.011,0.033),(0.000,0.007,0.017),(0.014,0.020,0.029), \\ (0.015,0.021,0.029),(0.016,0.024,0.035),(0.015,0.022,0.032), \\ (0.015,0.022,0.032) \end{bmatrix}$$

$$d_i^+ = \begin{bmatrix} (0.020,0.046,0.107),(0.026,0.034,0.046),(0.032,0.043,0.060), \\ (0.024,0.064,0.177),(0.035,0.047,0.063),(0.033,0.056,0.098), \\ (0.033,0.056,0.098), (0.039,0.055,0.078),(0.029,0.037,0.048), \\ (0.029,0.038,0.048),(0.032,0.043,0.059), (0.027,0.035,0.047), \\ (0.030,0.040,0.054) \end{bmatrix}$$

Therefore, the distances of each alternative from the positive ideal solution (d_i^+) and negative ideal solution (d_i^-) were calculated.

$$d_i^- = (0.26096,0.08432,0.16425,0.28776,0.19673,0.11566)$$

$$d_i^+ = (0.19746,0.37252,0.29291,0.16880,0.26340,0.34197)$$

Finally, the closeness index for each alternative was determined. The results are shown in the third column of Table 17. Figure 6 shows the rankings of potential suppliers using different methods in a more intuitive way.

[Insert Table 17 and Figure 6 about here.]

Based on the results shown in Table 17 and Figure 6, we can draw the following conclusions. Firstly, comparing the ranking results of FGRA (Table 15) with GRA

(Table 17), we find that, when the evaluation information is not processed by fuzzy set theory first but directly analyzed by GRA, the evaluation information of decision-makers cannot be fully expressed due to the uncertainties. In addition, in the complex SSS process, as the criteria weights were equally distributed, GRA cannot assign criteria weights objectively based on the practical situation of the chemical industry. Thus, the result of GRA is widely different from the result of FGRA.

Secondly, although the result of GRA (Table 17) is similar with the proposed approach (Table 15), however, the former is less robust. From sub-section 5.1, it can be seen that when the weight distribution varies to a certain extent, the final ranking changes at all. Therefore, it is not reasonable to use the average weight distribution in the GRA analysis, and the result obtained is unrealistic. In contrast, considering the characteristics of various dimensions and selecting appropriate methods, the results of the proposed approach show that both the best suppliers (S_4) can be selected and the worst suppliers (S_2) can be eliminated.

Thirdly, the consistency between the result of FTOPSIS (Table 17) and the result of FGRA (Table 15) demonstrates that FGRA can achieve the same performance in fewer steps, which consistent with the research findings of Banaeian et al. (2018).

In summary, in accordance with the distinctive characteristics of the chemical industry, the proposed approach chooses specific methods to evaluate suppliers in the three TBL dimensions, respectively and systematically, and then designs a reliable method to integrate their dimensional ranking results. Moreover, the proposed approach is stable and robust, as its results are more objective when dealing with the uncertain information of decision-makers, and more reasonable when allocating the weights of different criteria.

6. Discussion of results

Without truly sustainable suppliers, a SSC would not be able to meet the required sustainable goals (Kannan, 2018). As the chemical industry, which is one of the most important industry sectors in terms of huge energy consumption, potential sources of pollution and high risk in CSR, there is an urgent need to develop a systematic approach to evaluate and identify the most appropriate sustainable suppliers. However, previous literature has paid little attention to this specific but very important topic. To date, only Tong et al. (2019; 2020) have undertaken primary research on SSS in the chemical industry. However, their research focused on the performance of maintenance suppliers, without considering production safety and carbon tracking. In addition, the analysis and selection of raw material suppliers can not only help enterprises to choose economical, green and sustainable suppliers (Foroozesh et al., 2017), but also reduce the risk of supply disruption for the whole supply chain (Wu et al., 2020a). To bridge the research gaps, this study has combined appropriate methods to conduct a dimensional analysis approach for SSS, and thereby help managers make more reliable decisions. The applicability of the approach in the context of sustainable development has been illustrated through an empirical analysis, and its validity and effectiveness demonstrated through both sensitivity and comparative analysis.

The findings from the research are now considered against each of the research gaps that were identified from the Literature review as set out in Section 2.4. In this way, it is possible to identify the four contributions that are made by this research.

Firstly, the results presented demonstrate that the paper makes a contribution by bridging research gap (1) to provide a novel systematic integrated decision-making approach for SSS in the chemical industry based on the specific features of the industry. In addition, unlike the very limited existing research in the chemical industry, such as Tong et al. (2019; 2020), the proposed approach conducts separate in-depth analysis for each of the TBL dimensions before combining these results effectively, reducing the rate of information loss. Thereby, it can evaluate and identify the most appropriate sustainable suppliers in the chemical industry effectively (see Figure 3 as an example).

Secondly, the research presented bridges research gap (2) by utilizing specific methods or models that are each matched to the distinctive characteristics of each of the TBL dimensions in the chemical industry (argumentation and comparison analysis are summarized in Table 1), in order to ensure high efficiency and effectiveness in each dimensional analysis and to avoid large amount of information loss (You et al., 2015). Furthermore, this research not only provides appropriate dimensional analysis methods and framework, but also proposes an improved DEMATAL method to combine the evaluations of TBL dimensions reasonably and objectively. The flexible combination of qualitative and quantitative methods makes SSS decision-making more effective and reasonable.

Thirdly, the research has bridged research gap (3) by combining FMEA and IVPFST in order to evaluate suppliers' safety and risk management, in both production and delivery. Doing so is an essential requirement within the social dimension of the TBL for SSS in the chemical industry. Using these two methods in combination uses the advantages of one method (IVPFST) to compensate for the disadvantages of the other (FMEA) to deal with the issue of risk more effectively. FMEA is able to identify and assess the potential risk of production safety (Lo et al., 2020) and CSR (Franceschini & Galetto, 2010; Bozdag et al., 2015), whilst IVPFST is able to capture the vagueness and uncertainty of information during the evaluation and decision-making process (Foroozesh et al., 2017; Rahman et al., 2017). This novel integration makes SSS decision-making in the chemical industry more secure and reliable (Tables 8 and 9 as examples).

Fourthly, the research bridges research gap (4) by utilizing cloud computing to efficiently track the carbon footprint of potential suppliers which is required for the environment dimension of TBL. Unlike previous research, which paid more attention to strict emission caps, carbon taxes and cap-and-trade when considering the carbon footprint of suppliers (Lamba et al., 2019), the proposed cloud framework enables information to flow between suppliers and buyers in real time, facilitating the track and control of carbon emissions from raw materials, production and transportation. This is also a simple but effective way to provide data to enable focal companies to choose greener and more environmentally friendly suppliers, rather than relying on subjective judgement only (Tables 10 and 11 as examples). This feature will decrease the carbon cost of the whole chemical supply chain considerably.

7. Managerial Implications

Both the illustrative and sensitivity analysis results provide SSCs managers with some important management implications. First, in the chemical industry, we must pay more attention to production and delivery safety because once a leakage or explosion occurs due to the quality of production facilities or raw materials, it will not only cause extremely severe damage and an irreparable impact on the environment but also negatively affect the company's reputation and CSR (typical negative examples are shown in Table 1). Therefore, production safety is essential in the selection of sustainable suppliers in the chemical industry. In this research, production and delivery safety is one of main social criteria. By using FMEA to analyze risk, the raw materials or production equipment provided by suppliers are safe and reliable, and the frequency of accidents in the production process of the company is reduced.

Second, the carbon footprint tracking in the proposed cloud framework can help reduce the carbon emissions. Wu et al. (2020a) found that resource consumption in the production process is the most influential standard for sustainable development. Suppliers can connect to the enterprise through the private cloud system in the framework. After selecting the raw material’s name and entering the corresponding parameters, the focal company can know the carbon emissions. In the case of Company F, according to the carbon data from the private cloud, the enterprise chose the greenest supplier so that it could reduce carbon emissions in the production process, thereby reducing carbon tax. The supplier can also optimize the production process based on these data to reduce carbon emissions. In general, this private cloud can be used as a platform for real-time information exchange between supplier and buyer to accelerate the flow of information. If the focal company has urgent needs, the suppliers can respond accordingly to maintain the sustainability of the whole supply chain.

Finally, by analyzing the supplier selection criteria, based on the TBL principle, companies can understand the interrelationships between social, environmental, and economic dimensions more clearly. On the one hand, although economic factors (especially cost) are the criteria that most companies prioritize, in the chemical industry, supply chain managers are more concerned about environmental and social factors. They all realize that once the suppliers of the chemical industry have any problems in the environmental dimension, it will destroy the cooperative relationship. On the other hand, managers also consider that the triple dimensions are not simply inverse relationships. From Section 4 and 5, we know that the impact of social benefits on the economy and the environment is different from the impact of the economy and the environment on them. The positive mutual influence among the three dimensions indicates that suppliers can be one of the prerequisites for sustainable development.

8. Conclusions

Due to an increased awareness of ecological protection and resultant stringent legislations, the adoption of sustainable practices has become an important consideration for business organizations with regard to their supply chains (Zhang et al., 2016; Kannan, 2018). The chemical industry is a high-risk, high-pollution, and high-efficiency industry, where these considerations can help companies to determine their growth and sustainability over the long term. Thus, a systematic and sustainability focused evaluation system for supplier selection is highly required in the chemical industry. This research proposes an integrated approach combining appropriate decision-making methods efficiently and effectively. FGRA is used to evaluate potential suppliers' economic dimension. The result of risk assessment through FMEA is used as the input of IVPFST to obtain the ranking in social dimension. In the environmental dimension, the EWM is used to get the criteria weights objectively. Finally, the three TBL dimension weights were obtained through cloud based DEMATEL to reasonably combine the ranking results in different dimensions and identify the most appropriate sustainable suppliers. An empirical illustration was conducted to prove the model's applicability, as well as sensitivity and comparative analysis to show its efficiency and effectiveness.

This study also has its own limitations which offer interesting directions for future research. Firstly, the illustration is based on a single case study, thus, the findings cannot be generalized. So, further applications in other case companies are required. Secondly, considering the Hausdorff distance is also an efficient distance, applying it to obtain the intensity relationship matrix, would also be an interesting research direction. Thirdly, the fundamental requisite for the cloud-computing framework is not readily accessible to the chemical industry. Last but not least, fuzzy and grey DEMATEL have the potential to integrate the ranking results in different dimensions. Future research can try to validate and compare their practicality and effectiveness.

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Figures & Tables

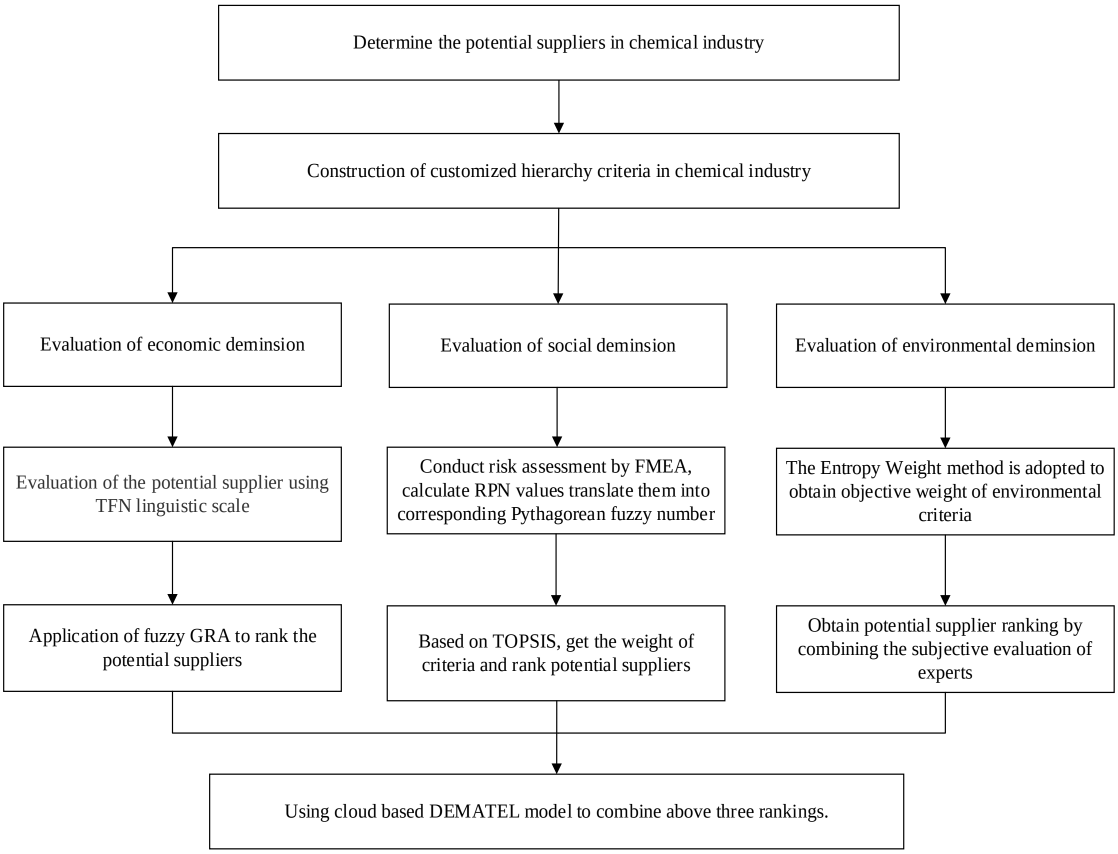

Figure 1: The proposed framework of sustainable supplier selection in chemical industry

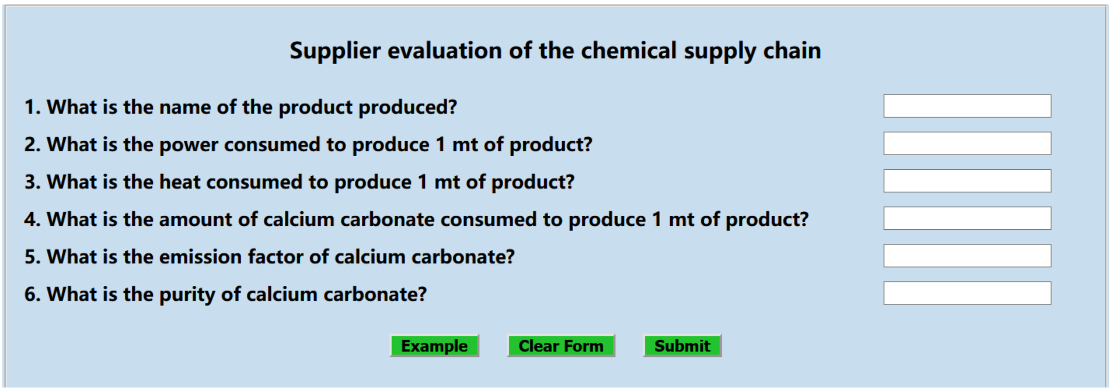

Figure 2: The information collected by carbon calculator on the cloud.

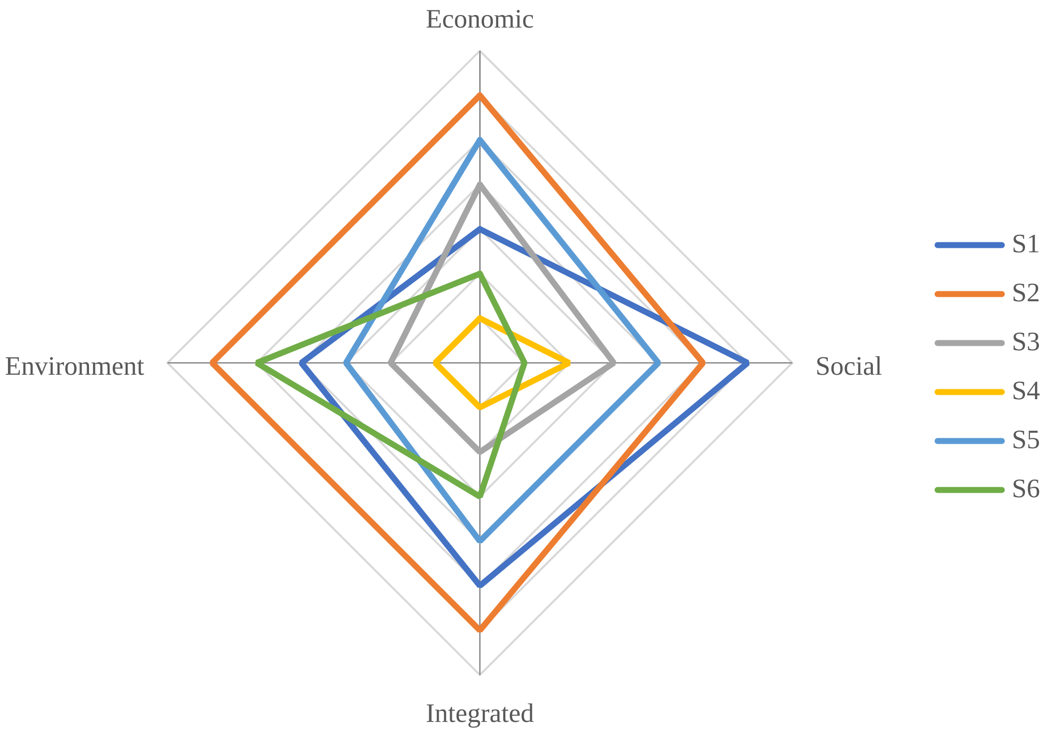

Figure 3: The integrated ranking and the respectively rankings on TBL dimensions

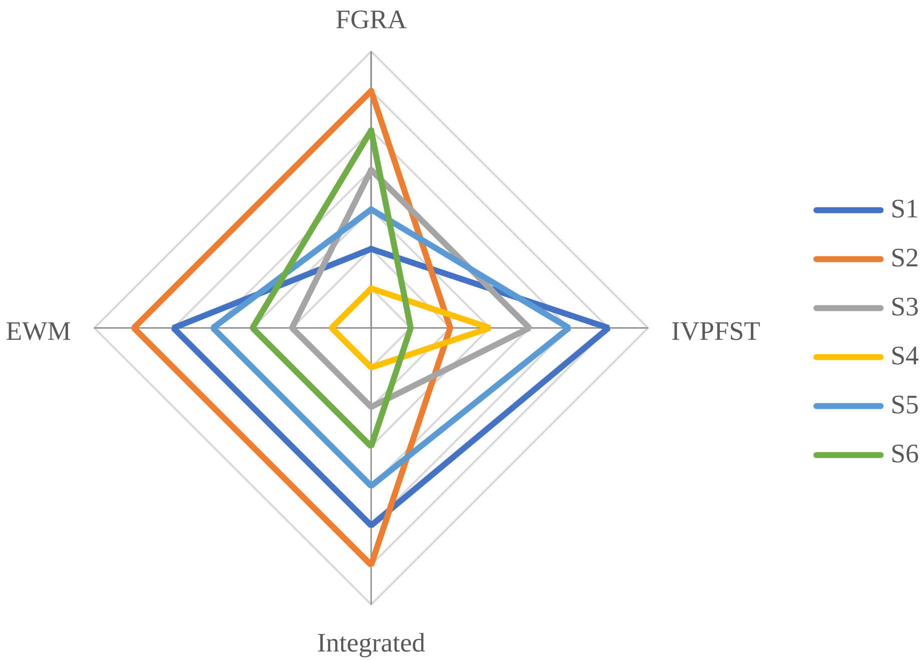

Figure 4: Sensitivity analysis on different dimensional methods

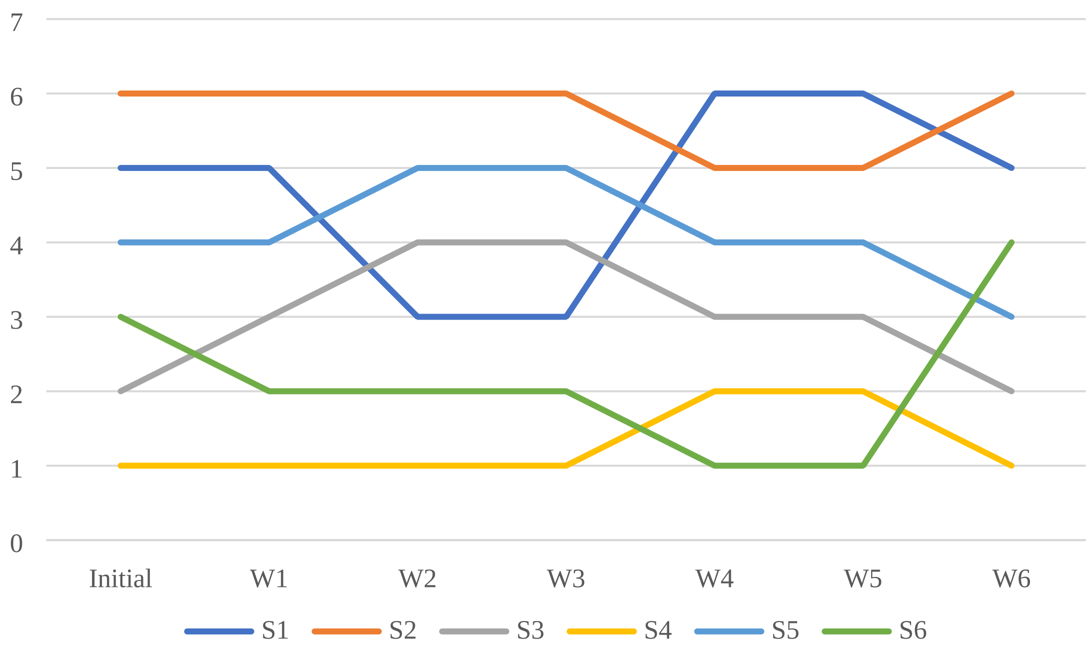

Figure 5: Sensitivity analysis on different weights scenarios

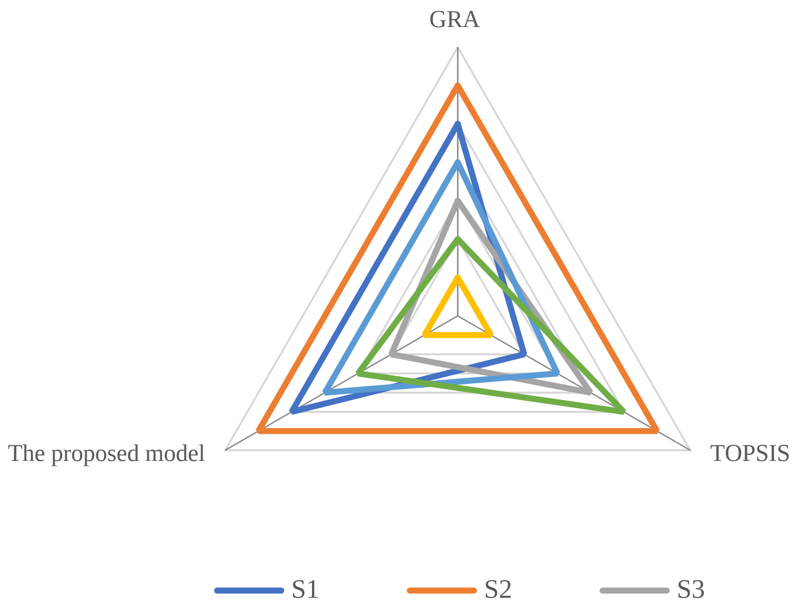

Figure 6: Comparative analysis between different methods

Table 1: Methods, reasons and comparisons

Dimension	Method	Reasons to apply the specific method	Comparison with existing works
Economic	FGRA	FGRA can be used to manage both incomplete information and problem/system ambiguities, which is often the case when dealing with subjective data or insufficient/vague information (Banaeian et al., 2018).	Follow the methodology of Banaeian et al. (2018)
Social	FMEA	1. Social risk assessment is important (Yuan et al., 2018) 2. FMEA is an effective risk analysis method for high-risk links (Kales, 1998)	1. Pythagorean fuzzy numbers can better deal with the ambiguity of the linguistic value of the decision-maker to the evaluation object (Yager, 2013) 2. Risk assessment based on the social dimensions of the chemical industry
	IVPFST	1. The social dimension is more qualitative than the economy and environment dimensions are. Decision-makers will have greater uncertainty and ambiguity in the decision-making process due to the lack of experience and data (You et al., 2015) 2. IVPFST is applicable to capture uncertain information in SSS (Rahman et al., 2017) 3. FMEA will have difficulty dealing with uncertain information (Franceschini & Galetto, 2010)	
Environment	Cloud computing	1. Carbon footprint is important (Yu et al., 2018) 2. The effectiveness and convenience of cloud computing for carbon footprint tracking (Singh et al., 2018).	1. First time that cloud computing combined with the EWM. 2. Carbon footprint of cloud computing chemical industry.
	EWM	1. The EWM can deal with the complex interrelationships between environmental indicators to determine the indicator weights (Isik, 2009) 2. Weight distribution according to the internal information of the indicator to eliminate human interference (Liao & Kao, 2011).	
Integration	DEMATEL based on cloud model	1. DEMATEL can transform the relationship between elements and causal dimension from a complex system into an understandable structural model (Chang et al., 2011). However, the DEMATEL method cannot consider ambiguity and randomness (Xie et al., 2018). 2. The cloud model can effectively express the uncertainty of language value (Wang & Liu, 2012) 3. The information loss problem of DEMATEL (Kadoić et al., 2018) can be solved by the cloud model.	1. Weights among dimensions are calculated by DEMATEL after using the integrated cloud to convert the language values. 2. Define the proportion of influenced degree as attribute weight.

Table 2: Conventional RPN evaluation criteria for occurrence.

Probability of failure	Possible failure rates	Rank
Extremely high: failure almost inevitable	≥ 1 in 2	10
Very high	1 in 3	9
Repeated failures	1 in 8	8
High	1 in 20	7
Moderately high	1 in 80	6
Moderate	1 in 400	5
Relatively low	1 in 2000	4
Low	1 in 15,000	3
Remote	1 in 150,000	2
Nearly impossible	≥1 in 1,500,000	1

Note: Ford Motor Company (1988).

Table 3: Numerical variables and corresponding IVPFNs.

RPNs	IVPFNs
1~57	([0.80, 0.95], [0.00, 0.15])
58~114	([0.70, 0.80], [0.15, 0.25])
115~171	([0.55, 0.70], [0.25, 0.40])
172~228	([0.45, 0.55], [0.40, 0.55])
229~285	([0.30, 0.45], [0.55, 0.70])
286~342	([0.20, 0.30], [0.70, 0.80])
343-1000	([0.00, 0.20], [0.80, 0.95])

Table 4: Criteria for sustainable supplier selection

TBL	Sustainable criteria	Authors/years
Economic	Price	(Hashemi et al., 2015)
	Quality	(Amindoust et al., 2012; Buyukozkan & Cifci, 2011)
	Delivery on time	(Hashemi et al., 2015; Wu & Barnes, 2010)
	Transit loss	(Tang et al., 2019)
	Technology capability	(Govindan et al., 2015; Kuo et al., 2010)
Social	CSR	(Andersen & Skjoettlarsen, 2009; Hsueh, 2014)
	Production safety	(Azadi et al., 2015; Wu et al., 2020a)
	Employee benefits	(Kuo et al., 2010; Yu et al., 2019)
Environment	Environmental management system	(Azadnia et al., 2015; Kuo et al., 2010)
	Green materials and technologies	(Awasthi et al., 2010; Humphreys et al., 2006)
	Design for environment	(Azadi et al., 2015; Humphreys et al., 2006)
	Carbon footprint	(Singh et al., 2018; Yu et al., 2018)
	Land and water pollution management	(Erol et al., 2011; Wu et al., 2020a)

Table 5: Supplier evaluations against economic criteria by decision-maker team

Suppliers	C_1	C_2	C_3	C_4	C_5
S_1	G	MG	MG	G	VG
S_2	VG	MG	F	G	P
S_3	MG	G	MG	MG	F
S_4	MP	MG	G	P	MG
S_5	G	G	F	F	F
S_6	MP	G	P	VG	MG

Table 6: The grey relational grade and ranking of suppliers in economic dimension

Suppliers	γ_i	Rank
S_1	0.3565	3
S_2	0.2412	6
S_3	0.3524	4
S_4	0.7864	1
S_5	0.3390	5
S_6	0.3916	2

Table 7: The RPN value of alternative suppliers in each social criterion

Suppliers	C_1	C_2	C_3
S_1	210	175	320
S_2	105	84	243
S_3	72	72	72
S_4	56	56	56
S_5	120	120	120
S_6	24	24	27

Table 8: Relative closeness coefficient and ranking of suppliers in social dimension

Suppliers	Relative closeness coefficient	Rank
S_1	0.0000	6
S_2	0.4592	5
S_3	0.7360	3
S_4	1.0000	2
S_5	0.4720	4
S_6	1.0000	1

Note: The relative closeness coefficient of S_4 and S_6 are both 1. Considering the lower RPN value of S_6, it ranks number 1.

Table 9: Supplier rankings against environmental criteria by decision-maker team

Suppliers	C_1	C_2	C_3	C_4	C_5
S_1	MG	G	MG	MG	MG
S_2	F	F	F	F	F
S_3	VG	G	MG	G	G
S_4	VG	VG	VG	G	VG
S_5	VG	G	MG	MG	MG
S_6	MG	MG	F	G	MG

Table 10: Evaluation scores and ranking of suppliers in environment dimension

Suppliers	Evaluation scores	Rank
S_1	5.21	4
S_2	4.00	6
S_3	6.05	2
S_4	6.81	1
S_5	5.66	3
S_6	5.02	5

Table 11: The evaluation of the interrelationships among TBL

	Eco			Soc			Env		
	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3
Eco	0	0	0	$[S_0, S_1]$	$[S_{-1}, S_1]$	$[S_0, S_1]$	$[S_0, S_1]$	$[S_{-1}, S_1]$	$[S_1, S_2]$
Soc	$[S_{-2}, S_{-1}]$	$[S_0, S_1]$	$[S_{-1}, S_0]$	0	0	0	$[S_{-2}, S_{-1}]$	$[S_0, S_1]$	$[S_{-2}, S_0]$
Env	$[S_0, S_1]$	$[S_1, S_2]$	$[S_0, S_1]$	$[S_0, S_1]$	$[S_1, S_2]$	$[S_{-1}, S_0]$	0	0	0

Table 12: Comprehensive cloud matrix based on DEMATEL

	Economic	Social	Environment
Economic	0	(54.28, 4.90, 0.35)	(62.28, 6.04, 0.43)
Social	(38.82, 4.96, 0.41)	0	(35.46, 7.45, 0.46)
Environment	(62.14, 5.34, 0.41)	(57.99, 5.41, 0.41)	0

Table 13: The comprehensive influence matrix *Z*.

	Economic	Social	Environment
Economic	0.8914	1.3936	0.7639
Social	0.6652	0.4901	0.2687
Environment	1.3094	1.4394	0.5288

Table 14: The weights of the three TBL dimensions in SSS

	Weights	Rank
Economic	0.3934	2
Social	0.1837	3
Environment	0.4229	1

Table 15: Rankings of alternatives when using single method only

	S_1	S_2	S_3	S_4	S_5	S_6
FGRA	2	6	4	1	3	5
IVPFST	6	2	4	3	5	1
EWM	5	6	2	1	4	3
Integrated	5	6	2	1	4	3

Table 16: Sensitivity analysis on different weighting scenarios

	Initial weights	W_1	W_2	W_3	W_4	W_5	W_6
Economic	0.3934	0.333	0.800	0.800	0.050	0.150	0.050
Social	0.1837	0.333	0.150	0.050	0.800	0.800	0.150
Environment	0.4229	0.333	0.050	0.150	0.150	0.050	0.800

Table 17: Comparative analysis between GRA and FTOPSIS

Suppliers	GRA γ_i (ranking)	FTOPSIS *CI* (ranking)
S_1	0.4746 (5)	0.5693 (2)
S_2	0.3951 (6)	0.1846 (6)
S_3	0.6630 (3)	0.3593 (4)
S_4	0.9145 (1)	0.6303 (1)
S_5	0.5600 (4)	0.4276 (3)
S_6	0.6801 (2)	0.2527 (5)