Supplier Selection in Sustainable Supply Chains: A Risk-Based Integrated Group Decision-Making Model

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Abstract: With the recent emphasis on supply risk management in sustainable supply chains (SSCs), the evaluation and selection of appropriate suppliers are more important than ever. However, most existing research does not take all three sustainability perspectives of supply risk into account simultaneously and they rarely consider the correlation among supply risk factors in risk assessment. Therefore, considering the uncertain information decision-making environment, this research paper proposes a risk-based integrated group decision-making model for sustainable supplier selection (SSS). First, the weights of decision-makers (DMs) are taken as linguistic terms denoted by intuitionistic fuzzy numbers (IFNs). Second, after obtaining the aggregated intuitionistic fuzzy decision-making matrix considering the expert weights, this study uses the entropy weight method to calculate the criteria weights objectively. Then, the improved failure mode and effects analysis (FMEA) is adopted for the risk assessment to exclude high-risk suppliers. Finally, the extended alternative queuing method (AQM) is applied to rank the qualified suppliers in SSCs. This model can not only enable enterprises to reduce supply risk in SSS practices and identify and prevent the failure modes that lead to supply risk, but also reduce the uncertainty of decision-making, in order to make supplier selection more accurate. The feasibility and effectiveness of the proposed model are illustrated through application in a leading Chinese electrical appliance manufacturing company.

Keywords: Sustainable supply chain; Supplier selection; Supply risk; FMEA; Alternative queuing method

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1. Introduction

Growing public pressure from customers, competitors, and governments has caused companies to pay more attention to sustainability practices (Wolf 2013; Babazadeh et al. 2017; Tseng et al. 2019). Consequently, sustainable supply chain management (SSCM) has been applied by focal companies to ensure that their suppliers act in a socially and ecologically beneficial manner (Eskandarpour et al. 2015; Xiong et al. 2020).

The increasing complexity and embedded supply risks make SSCM more challenging (Zimmer et al. 2017). First, within the economic dimension, the globalization of supply chains has prompted companies in industrialized countries to increasingly outsource their production processes, resulting in serious potential quality failure risks (Steven et al. 2014). Toyota's product recall crisis has been interpreted as being the result of supply risk from the perspective of the economic dimension. Second, the social aspects of supply risk need to be analyzed systematically. Non-compliance with social expectations causes the enterprise to face the risk of losing brand reputation and legitimacy (Awasthi et al. 2018). One example of this concerns is the supermarkets in Europe and North America (Wal-Mart, Carrefour, Tesco), which were accused of selling prawn products that were produced under inhumane working conditions. Nongovernmental organizations and media campaigns damaged the supermarkets' brand image, forcing them to remove the corresponding prawn products from their shelves (Gold et al. 2015). Third, integrating environmental issues into the interorganizational practices of SSCM is the effectual measure for finding a potential solution for minimizing environmental impacts (Wu and Barnes, 2016). Ignoring supply risk in environmental dimensions, such as carbon footprint, toxic emissions, energy use and efficiency, and waste generation, will affect the environmental performance of SSCM. A tragic example was the one of the largest global offshore oil spills caused by British Petroleum (Zimmer et al. 2017). In short, modern supply chains have become complex networks of suppliers, manufacturers, and consumers in different geographical regions, creating a high degree of uncertainty and increased vulnerability to unexpected events and supply risks (Fang et al. 2015). These events and risks have brought huge losses. Consequently, identifying and evaluating supply risks are indispensable to sustainable supplier selection (SSS).

However, traditional SSS approaches suffer from four main drawbacks. First, existing research has discussed various facets of supply risk management, involving risk identification, assessment, monitoring, and prevention, but SSS concerning supply risk has received insufficient attention so far. On the one hand, little research considers SSS and supply risks simultaneously. On the other hand, previous studies have rarely considered the correlation among supply risk factors, which will lead to inaccurate supply chain risk assessment and supplier selection. Second, existing research on SSS seldom takes the weights of decision-makers (DMs) into account, which will affect the effective and accuracy of decision-making. Third, traditional failure mode and effects analysis (FMEA) evaluates risks by calculating a traditional risk priority number (RPN). Since each criterion is related to the others, traditional FMEA cannot effectively predict the risk in sustainable supply chains (SSCs) (Chen & Wu, 2013). Fourth, the calculation process of the alternative queuing method (AQM) is relatively simple and sorting the results can be more intuitive via a directed graph, thus it has high potential use in solving the problems of risk-based SSS. However, there are few applications in this research field.

To overcome the above research gaps, this study proposes a risk-based integrated group decision-making model. Considering the breadth of supply risk faced by organizations, we mainly consider operational risks in supply risk. In this context, this research applies intuitionistic fuzzy sets to tackle uncertain and imprecise decision information in group decision-making, while integrating the entropy weight method and FMEA to identify high-risk suppliers. Finally, the AQM is employed to rank the qualified suppliers.

In comparison with the existing literature, the proposed model makes the following contributions. First, this study develops a risk-based integrated group decision-making model for SSS. In accordance with the triple-bottom-line (TBL) principle, we solve the problem of SSS while comprehensively addressing supply risk. Second, this study considers both criteria weights and DMs' weights simultaneously and reasonably. On the one hand, this research combines the characteristics of intuitionistic fuzzy sets and uncertain linguistic variables to determine the weights of DMs, which can more accurately reflect the actual preferences of different DMs. On the other hand, after establishing the intuitionistic fuzzy decision-making matrix, the entropy weight method is used to determine the weights of each criterion objectively, thereby integrating both objective and subjective decision-making methods and perspectives. Third, this study quantifies the degree of risk of each criterion using FMEA, in order to provide the additional risk-related information for decision-making. Also, the new RPN formula is proposed to compare suppliers' supply risk at a smaller order of magnitude to obtain more refined results. Last but not least, this study applies the AQM, which is seldom used in the field of SSS, in the intuitionistic fuzzy environment, thus expanding the scope of the application of the AQM and improving the quality of SSS decision-making. To our knowledge, no previous studies have used this integration approach for SSS.

The rest of this research paper is organized as follows: Section 2 presents the literature of supply risk and SSS; Section 3 develops a risk-based group decision-making model for SSS; Section 4 presents a case study in the manufacturing industry to validate the proposed model; Section 5 offers sensitivity analysis and managerial implications, while the final section concludes the study and presents suggestions for future research.

2. Literature Review

2.1 Supply risk in sustainable supply chains

Researchers generally agree that the capability to identify possible sources of supply disruptions and manage risks represents a critical aspect of SSCM (Shafiq et al. 2017).

Previous studies have investigated different sources of supply risks. Roehrich et al. (2014) emphasized “reputational risk” and found it is a central driver in a company’s decision to implement SSCM practices. It highlighted reputational risk exposure in the supply chain from a social perspective. Nepal and Yadav (2015) considered multiple types of costs and risks, including currency fluctuation, price inflation, political risks, such as labor strikes and wage fluctuations, port delays, and port infrastructure risks. They mainly considered supply risk at the economic level, which could impact the costs and operational efficiencies of global supply chain systems. Awasthi et al. (2018) integrated additional global risks associated with off-shoring decisions into a global SSS model. They complemented the supply risk with the category of additional global risks linked to off-shoring decisions. In summary, the current research mainly believes that supply risk comes from various uncertain factors in the supply chain, which affect the normal operations of the supply chain.

Although supply risk has been recognized as an important issue in SSCM, the above research does not contain a uniform definition and classification of supply risk. Recently, two main categories of supply risk were summarized as operational risks and disruption risks (Fang et al. 2015; Vahidi et al. 2018). For instance, Kleindorfer and Saad (2005) presented a specific classification of disruption risks, including operational contingencies (e.g., equipment breakdown and systematic failure), natural disasters (e.g., hurricanes, earthquakes, and storms), terrorism, and political instability. Bode and Wagner (2015) argued that supply chain disruption was the combination of an unintended and unexpected triggering event that occurs somewhere in the upstream supply chain, the inbound logistics network, or the purchasing environment, which set the stage for a large set of issues, including quality problems with suppliers, delivery outages, supplier defaults, labor strikes, or plant fires. At the same time as the concept of disruption risks emerged, Tang (2006) explicitly identified operational risks (e.g., stochastic customer demand, uncertain supply, and changing costs) and disruption risks (arising from manmade or natural disasters, such as labor strikes and floods). Hosseini et al. (2019) further elaborated on the operational risks and disruption risks. They argued that the operational risks referred to the inherent "daily" events occurring within the supply chain, while the disruption risks referred to the major destructive events. Song et al. (2017) divide risk factors into four main dimensions, namely operational risk factors, economic risk factors, environmental risk factors, and social risk factors. They summarized the details of the recognized supply risk from TBL perspectives.

Meanwhile, some researchers have also made contributions to supply risk management strategies. Charpin et al. (2020) extended the political risks by inducting two dimensions of host-country political risk. They offered provocative insights into contemporary global supply chain risk mitigation strategies at the host-country level. Moreover, Shafiq et al. (2017) investigated operations risk and sustainability risk and conceptualized supplier sustainability risk as the potential occurrence of an incident associated with social and/or environmental shortcoming or failure by a supplier. This research explored the impact of supply sustainability risks on the use of monitoring practices to manage supplier environmental and social behavior.

In summary, previous research on supply risk mainly concentrates on the characteristics of the supply chain, including risk factors, risk categories, risk analysis, risk management measures, and so on. Moreover, previous studies mainly focused on the operational risks associated with costs and how these factors affect the operation of enterprises. Although some studies provide a range of supply risk management strategies, offering some insights into supplier selection, there are still some limitations. First, most of the existing research has not considered supply risk based on TBL (Cheraghalipour and Farsad 2018). Second, few studies have taken correlations among supply risk factors into account. Therefore, to bridge the above research gaps, this study plans to solve risk-based SSS from the TBL perspective (economic, environmental, and social). Given the breadth of supply risk facing the organization, this study plans to focus on operational risks, which were found to have the highest weight among risk factors (Mavi et al. 2017). In addition, this research will consider the correlation among supply risk factors.

2.2 Sustainable supplier selection

Researchers have adopted and developed many decision-making methods for SSS, ranging from basic single-objective methods to extended multi-objective methods. Handfield et al. (2002) used the analytic hierarchy process (AHP) to evaluate environmental criteria for green supplier assessment. Zarbakhshnia and Jaghdani (2018) extended a two-stage DEA network model in the presence of uncontrollable inputs and undesirable outputs with considering the set of intermediate elements between two stages. Recently, the use of hybrid methods that combine two or more techniques has received more attention due to their flexibility (Nguyen et al. 2014). Dai and Blackhurst (2012) presented an integrated analytical approach combining the AHP with quality function deployment for SSS. Kuo and Lin (2012) provided a green supplier selection method using the analytic network process (ANP), as well as data envelopment analysis (DEA). Govindan et al. (2017) proposed an integrated preference ranking organization method for enrichment of evaluations, or PROMETHEE-based multiple criteria ranking approach for evaluation and selection of the most preferred green supplier. Pishchulov et al. (2019) proposed a revised AHP method to overcome criticism of its DEA-based preference aggregation procedure in SSS.

Although the above methods have provided profound insights into the supplier selection literature, the uncertainty and fuzziness of DMs' assessments have still not received enough attention. Supplier selection is inherently more complex and difficult under conditions of uncertainty and ambiguity, as supply chains form and reform (Wu and Barnes 2012). To deal with such problems, fuzzy set theory is one of the most frequently used approaches. For instance, Buyukozkan and Cifci (2012) integrated a novel hybrid multiple-criteria decision-making (MCDM) approach combining decision making trial and evaluation laboratory (DEMATEL), technique for order performance by similarity to ideal solution (TOPSIS), and ANP in the fuzzy context to evaluate green suppliers. Hashemi et al. (2015) utilized ANP and improved gray relational degree analysis (GRA) to weight the criteria and rank the suppliers, respectively. Badri Ahmadi et al. (2016) discussed a structured and integrated decision-making model for evaluating sustainable suppliers in the telecommunications industry by combining the AHP and improved GRA approaches. Gupta et al. (2016) integrated the AHP and FMOILP approaches for the vender selection problem with multiple vendor and multiple item under price-breaks considering economic, technological, social, and environmental factors. Qin et al. (2017) extended the interactive multicriteria decision-making, or TODIM, technique to solve the green supplier selection problem. Ghadimi et al. (2018) evaluated the sustainability performance of the potential suppliers by utilizing the fuzzy inference system model and a multi-agent systems approach. Banaeian et al. (2018) provided a comparison between the performance of three fuzzy MCDM methods, including fuzzy TOPSIS, fuzzy multi-criteria optimization and compromise solution, or VIKOR, and fuzzy GRA. Chen et al. (2019) constructed a complete green supplier fuzzy selection model by using fuzzy sets and Six Sigma quality indices. Besides the above research, there are also some methods based on rough sets for overcoming the uncertainties in the decision-making process of SSS. Song et al. (2017) introduced an SSS framework based on the pairwise comparison method, DEMATEL, and rough set theory. In contrast, the fuzzy sets focus on describing the vagueness of information, while rough sets emphasize the nondiscrimination and imprecision of data.

However, if we want to deal with the hybrid fuzzy information using the above methods, this information will be lost in the conversion process. As a consequence, these MCDM approaches can only solve the problems that evaluation information can only be expressed using one kind of fuzzy information. In recent years, the AQM has been considered as a new technique for studying the MCDM problem. The AQM can be used to deal with hybrid fuzzy MCDM problems. In such problems, the evaluation information of alternatives under different criteria can be presented by different types of fuzzy information (Gou et al. 2016). For the ranking information, the AQM has a relatively simple computation procedure and can obtain a robust ranking result based on both quantitative and qualitative criteria (Duan et al. 2019). It can flexibly manage the intricate MCDM problems with substantial numbers of criteria and alternatives, in order to deal with the hybrid fuzzy information effectively. However, the application of this method in the field of SSS is nonexistent. Therefore, this study plans to combine the AQM with appropriate methods to obtain the rankings of alternative suppliers according to the directed graph and 0-1 priority relation matrix.

2.3 Sustainable supplier selection considering supply risk

Considering the risks alongside other factors in SSS is an essential condition for obtaining a widespread view of potential suppliers. However, risk issues have not received enough attention in SSS research. Wu et al. (2006) used AHP to assess supply risk, while Awasthi et al. (2018) developed an integrated fuzzy AHP-VIKOR approach-based framework for sustainable global supplier selection that takes sustainability risks from sub-suppliers into account.

In addition to these supplier risk assessment methods, FMEA is one of the most commonly used methods for evaluating risks in SSCs (Liu et al. 2019). FMEA has two methodical features (Li and Zeng 2016). First, the relationships of failure modes are casual. Second, failures are prioritized based on their severity, frequency, and ease of detection. The purpose of FMEA is to eliminate or reduce failures, starting with the highest priority failure. In this context, Chen and Wu (2013) explored a modified FMEA method to select suppliers and applied the AHP method to determine the weight of each criterion and sub-criterion. Foroozesh et al. (2018) introduced a new FMEA model based on multi-criteria decision-making by a group of supply chain experts and asymmetric uncertainty information. Arabsheybani et al. (2018) used a fuzzy multi-objective optimization model, while implementing FMEA to evaluate the risks of a supplier. Yazdani et al. (2019) proposed an integrated analytical approach for selecting green suppliers strategically consisting of the DEMATEL, FMEA and evaluation based on distance from average solution, or EDAS, methods.

In summary, FMEA considers the possible failure modes of products or services and determines the frequency and causes of their occurrence. It can be used for both pre-risk prevention and post-improvement. There are also many potential failure risks in the supply chain. Therefore, FMEA can be used to analyze the causes and mechanisms of the potential failure of supply risk in SSS. However, the traditional FMEA has shortcomings in risk-factor weighting, risk evaluation, and fault mode sequencing. The traditional FMEA calculates RPN according to the three risk assessment factors during the risk assessment. The basic calculation process has been criticized, as final RPN does not consider the importance of the corresponding evaluation criteria. Therefore, this study plans to take FMEA's advantages, while overcoming its shortcomings by improving the calculation process of FMEA, and combine the criteria weights with the final calculation results to improve the effectiveness and efficiency of risk-based SSS.

Table 1 provides a summary of representative studies on group decision-making methods of supplier selection.

[Insert Table 1 about here]

3. A risk-based integrated group decision-making model for supplier selection in SSCs

3.1 The proposed framework

Based on intuitionistic fuzzy set theory, the proposed model includes the following main stages. In the first stage, a decision-making group is established to determine the criteria related to supply risk from the TBL perspective and a language decision-making matrix for potential suppliers under each criterion is collected. Second, the defined intuitionistic fuzzy numbers, or IFNs, for five-point inflamed term scale are proposed to calculate the weight of each DM. Third, the weights of DMs are aggregated into the fuzzy decision-making matrix and, then, the weights of criteria are calculated by using the entropy weight method objectively. In the fourth stage, the improved FMEA is adopted to obtain the RPN and the weights of the RPN are calculated by combining them with the weights of the criteria. High-risk suppliers will be excluded at this stage. In the final stage, through the pair-to-pair comparison of qualified suppliers in each criterion, the 0-1 priority relation matrix and the directed graph are constructed using the AQM and the final ranking of qualified sustainable suppliers is obtained. The proposed framework is shown in Figure 1.

[Insert Figure 1 about here]

3.2 Determining the weights of decision-makers

The weights of DMs play a very important role in multiple attribute group decision-making. Considering various DMs come from different specialty fields, each DM has his/her unique characteristics with regard to knowledge, skills, experience, and personality.

Intuitionistic fuzzy sets are an extension of the conventional fuzzy sets theory and it is a proper approach for coping with vagueness in SSCs (Memari et al. 2019). To define an intuitionistic fuzzy set, assuming *A* is an intuitionistic fuzzy set in a finite set *X*, then *A* can be defined as follows:

$$A=\left\{\left\langle x,\mu_{A}\left(x\right),v_{A}\left(x\right)\middle|x\in X\right\rangle\right\} \tag{1}$$

Where $\mu_A(x): X \rightarrow [0, 1]$ is a membership function and $v_A(x): X \rightarrow [0, 1]$ is a non-membership function, respectively, satisfying $0 \leq \mu_A(x) + v_A(x) \leq 1$, □x□X.

The numbers $\mu_A(x)$ and $v_A(x)$ represent, respectively, the degree of membership and the degree of non-membership of the element x to A for all x□ X. Assuming that $\pi_A(x)$ is the hesitation degree of whether x belongs to A, then $\pi_A(x)$ can be expressed as follows:

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \quad (2)$$

It is obvious that for every $x \in X$:

$$0 \le \pi_A(x) \le 1 \quad (3)$$

To begin the process for calculating the weights of DMs, let us assume that a group supplier selection problem has l DMs DM_k ($k = 1, 2, ..., l$), m alternatives A_i ($i = 1, 2, ..., m$), and n evaluation criteria C_j ($j = 1, 2, ..., n$) .

Step 1. Let $D_k = [\mu_k, \nu_k, \pi_k]$ be the intuitionistic fuzzy number for the ranking of the k^{th} DM. Then the weight of the k^{th} DM can be calculated as:

$$\lambda_k = \frac{\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k + \pi_k\left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)} \quad (4)$$

Step 2. Create the aggregated intuitionistic fuzzy decision-making matrix according to the DM's opinions by using an intuitionistic fuzzy weighted averaging (IFWA) operator.

In this study, the importance of the DMs, criteria, and sub-criteria are taken as linguistic terms represented using IFNs. For instance, these linguistic terms can be denoted by IFNs as depicted in Table 2.

[Insert Table 2 about here]

In the group supplier selection process, all the DMs' individual opinions need to be merged into a single group opinion, so that an aggregated intuitionistic fuzzy decision-making matrix can be formed. The aggregation is completed using equation (5) below (Büyüközkan and Göçer 2017). $\lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_l\}$ is the weight of each DM.

$$\begin{aligned} r_{ij} &= IFMA_\lambda\left(r_{ij}^{(1)}, r_{ij}^{(2)}, \cdots, r_{ij}^{(l)}\right) = \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \cdots \oplus \lambda_l r_{ij}^{(l)} \\ &= \left[1 - \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda k}, \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda k}, \prod_{k=1}^{l}\left(1-\mu_{ij}^{(k)}\right)^{\lambda k} - \prod_{k=1}^{l}\left(\nu_{ij}^{(k)}\right)^{\lambda k}\right] \end{aligned} \quad (5)$$

3.3 Determining the weights of criteria and measuring supply risk

3.3.1 Determining the weights of criteria

Intuitionistic fuzzy entropy determines the criteria weights according to the credibility of the input data. Different from the traditional entropy method, it measures the degree of separation between intuitionistic fuzzy sets and fuzzy sets (Zhao et al. 2017). This study references an intuitionistic fuzzy set discriminant measure approach based on information theory and the entropy measure for intuitionistic fuzzy sets is as follows:

$$\begin{aligned} E(A) = -\frac{1}{n\ln 2}\sum_{i}^{n}[\mu_A(x_i)\ln\mu_A(x_i) + \nu_A(x_i)\ln\nu_A(x_i) \\ -(1-\pi_A(x_i))\ln(1-\pi_A(x_i)) - \pi_A(x_i)\ln 2] \end{aligned} \tag{6}$$

In this subsection, the entropy weight method will be extended to compute the weights of criteria based on intuitionistic fuzzy sets objectively and the main steps of the entropy weight method are briefly outlined as follows:

Step 1. Establish the intuitionistic fuzzy decision-making matrix. In the group SSS decision-making process, the DMs' individual opinions need to be aggregated into group evaluations to build a collective intuitionistic fuzzy decision-making matrix.

Step 2. Calculate the intuitionistic fuzzy entropy values. The following equation is applied for the calculation of the intuitionistic fuzzy entropy value for each criterion:

$$\begin{aligned} E_j = -\frac{1}{m\ln 2}\sum_{i}^{m}[\mu_{ij}\ln\mu_{ij} + \nu_{Aij}\ln\nu_{ij} \\ -(1-\pi_{ij})\ln(1-\pi_{ij}) - \pi_{ij}\ln 2],\ j = 1,2,...,n. \end{aligned} \tag{7}$$

Step 3. Obtain the objective weights of criteria by:

$$w_i^o = \frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)},\ j = 1,2,...,n, \tag{8}$$

Where $0 \le w_j^o \le 1$ and $\sum_{j=1}^{n} w_j^o = 1$.

3.3.2 Supply risk measurement using FMEA

In this subsection, a revised FMEA technique is applied to measure the supply risk of potential suppliers. The detailed process is as follows: Based on the criteria constructed already, the first step is to define the failure modes. The failure modes should be further clarified and one or more possible failure effects should be listed for each failure mode. Determining the effects and severity rankings is the second step (S). If the failure mode has multiple effects, only the highest severity rating for the failure mode is written in the FMEA table. The third step is to determine the causes and likelihood rankings (L). For each failure mode, identify all potential root causes and determine the likelihood rankings of identified causes. Finally, identify the possible controls and assign detection ranking for each control (D). These controls may prevent the cause from occurring, reduce the likelihood of the cause occurring, or detect the failure before the cause has occurred but the customer has not been affected. For each control, the detection rankings should be determined. This study uses a 1-10-point scale in the scheme design and a larger score illustrates higher risk. Table 3 presents an example evaluation scheme that shows how the scores are mapped to various risk situations.

[Insert Table 3 about here]

Calculating RPN is the approach for changing the FMEA scheme to quantitative numbers. The traditional multiplication of S, L, and D to obtain the RPN has received considerable criticism (Kmenta and Ishii 2004). In this study, we applied a new RPN formula (Arabsheybani et al. 2018). Let us define *R* as equation (9) and *ep* as equation (10). The RPN formula is shown in equation (11).

$$R = S * L \tag{9}$$

$$ep = -0.1 * D + 1.55 \tag{10}$$

$$RPN = \left(\frac{(R-1)}{99} \right)^{ep} * 100 \tag{11}$$

3.4 Qualified supplier ranking using the AQM

This study extends the AQM with intuitionistic fuzzy sets to obtain the ranking of qualified sustainable suppliers. The detailed steps for ranking sustainable suppliers are explained as follows:

Step 1: Establish the collective intuitionistic fuzzy sets' evaluation matrix.

Step 2: Make pairwise comparisons of suppliers on each criterion. For the alternative pair (A_i, A_v), $(A_i \succ A_v)_j$ denotes that A_i is better than A_v on the criterion C_j; $(A_i \prec A_v)_j$ denotes that A_i is worse than A_v on the criterion C_j; $(A_i \approx A_v)_j$ represents that there is no difference between A_i and A_v on the criterion C_j.

Step 3: Compute three kinds of overall weights. The overall pros weight $w(A_i \succ A_v)$ of all alternative pairs $(A_i \succ A_v)$ can be computed by adding up all the weights of $(A_i \succ A_v)$ regarding the criterion C_j. That is,

$$w(A_i \succ A_v) = \sum_{j \in (A_i \succ A_v)_j} w_j \tag{12}$$

Analogously, the overall cons weight $w(A_i \prec A_v)$ and the overall indifference weight $w(A_i \approx A_v)$ can be computed.

Step 4: Derive the overall pros and cons indicated values of each supplier pair.

$$P(A_i, A_v) = \frac{w(A_i \succ A_v) + \sigma w(A_i \approx A_v)}{w(A_i \prec A_v) + \sigma w(A_i \approx A_v)} \tag{13}$$

Where σ denotes the important degree of $(A_i \approx A_v)$, satisfying $0 \leq \sigma \leq 1$.

Step 5: Find the precedence relationships among alternative suppliers. Given the threshold value $\theta > 1$, the relationships between the m alternative suppliers can be computed as follows:

$$\begin{cases} A_i \succ A_v, P(A_i, A_v) \geq \theta \\ A_i \approx A_v, 1/\theta < P(A_i, A_v) < \theta \\ A_i \prec A_v, 0 < P(A_i, A_v) < 1/\theta \end{cases} \tag{14}$$

Step 6: Compute the ranking value of each alternative supplier. Finally, the ranking value $\eta_i\left(i = 1, 2, \ldots, m\right)$ of each supplier is determined using the following formula：

$$\eta_i = \tau_i - \upsilon_i \tag{15}$$

Where τ_i is the quantity of the directed arcs starting from A_i and υ_i is the quantity of the directed arcs pointing to A_i.

4. Empirical illustration

Company J is a well-known technology company group integrating consumer electronics, robotics, and automation systems, intelligent supply chain, and the chip industry. As a result of the COVID-19 pandemic, the domestic appliance industry faces more internal and external uncertainties and fluctuations. However, in the medium and long term, the upgrading of industrial structure, the stability of household income, the diversification of consumption, the guidance of national policies, and the upgrading of product standards in the household appliance industry have all brought new opportunities and growth points. The home appliance industry is an important downstream industry for steel. Therefore, the raw material of the home appliance products of Company J is taken as the research object.

The company's supply risks mainly include the following aspects, such as the risk of steel price fluctuations, as well as operational risks. Imperfect internal processes, employees, systems, and external events may cause the company to bear losses in the process, along with the risk from the increase in the demand for green environmental protection materials, and so on. In order to meet the needs of product upgrading and supply risk reduction in the supply chain, Company J needs to choose more suitable and sustainable suppliers.

Five steel companies S_1, S_2, S_3, S_4, and S_5 have been determined as alternatives for further assessment. Three DMs (DM_1, DM_2, and DM_3) come from the procurement, production, and financial departments of Company J, respectively. Based on the reviewed literature and the actual situation of the company, eleven criteria have been selected from the TBL perspective (shown in Table 4).

[Insert Table 4 about here]

4.1 Determining the weights of decision-makers

To weight the DMs, the linguistic terms in Table 1 have been used. The importance of each DM is evaluated considering three factors, including: i) relevant experience in supplier selection decision-making, ii) educational background, and iii) organizational position (Memari et al. 2019). The linguistic term for the first and the second expert is scored as being of high importance and the third expert is scored as being of medium importance. To calculate the weights of the DMs, Eq. (4) was used. Table 5 shows the importance degree of the DMs and their corresponding weights.

[Insert Table 5 about here]

4.2 Determining the weights of criteria and measuring supply risk

In this stage, the intuitionistic fuzzy decision-making matrix is constructed by the DMs. The evaluation results obtained are shown in Table 6 and, afterward, these ratings were converted to intuitionistic fuzzy numbers (shown in Table 7).

[Insert Table 6 and 7 about here]

In the group decision-making procedure, all of the member opinions need to be merged into a group decision opinion. To do so, an aggregated intuitionistic fuzzy decision-making matrix is required. For this purpose, this study proposes an IFWA operator to aggregate the individual decisions. Applying Eq. (5), the aggregated intuitionistic fuzzy decision-making matrix is obtained (shown in Table 8).

[Insert Table 8 about here]

After obtaining the aggregated intuitionistic fuzzy decision-making matrix, the criteria weights can be calculated using the objective weighting method described in subsection 3.3. The intuitionistic fuzzy entropy value of each criterion is obtained using Eq. (7) and the final criteria weights are calculated using Eq. (8). The results of these calculations are shown in Table 9.

[Insert Table 9 about here]

According to the RPN formula in Eq. (11), the risk assessment information for FMEA is shown in Table 10.

[Insert Table 10 about here]

In accordance with the weights of the criteria, the weighted RPN (*Rj*) is obtained by multiplying RPN with the criteria weights. For example, the results of each RPN weight for S_3 are shown in Table 11. The average RPN weights of five potential suppliers are 0.45, 0.21, 1.85, 0.32, and 0.55. It is clear that S_3 has a greater risk and can be identified as a unqualified supplier at this stage.

[Insert Table 11 about here]

4.3 Qualified suppliers ranking

According to the aggregated intuitionistic fuzzy decision-making matrix (Table 8), the 0-1 precedence relationship matrices, with respect to the criteria, are established. Using Eq. (12), the overall pros weights of all supplier pairs $w\left(A_i \succ A_v\right)$ (i,u = 1, 2, 4, 5) are computed (shown in Table 12). Similarly, the overall cons weight $w\left(A_i \prec A_v\right)$ (i, u = 1, 2, 4, 5) and the overall indifference weight $w\left(A_i \approx A_v\right)$ (i, u = 1, 2, 4, 5) are obtained (shown in Table 12 as well).

[Insert Table 12 about here]

Allowing $\sigma=0.5$, according to Eq. (13), the overall pros and cons indicated values among alternative suppliers are calculated and depicted in Table 13.

[Insert Table 13 about here]

Allowing $\theta=1.5$, according to Eq. (14), the final 0-1 precedence relationship matrix for the alternative suppliers is constructed. Then, the directed graph of the sustainable suppliers is constructed accordingly (shown in Figure 2). And the priority values of the five alternative suppliers are calculated in accordance with Eq. (15), as: $\eta_1 = 1, \eta_2 = 3, \eta_3 = -1, \eta_4 = -3$. Therefore, the ranking of the qualified suppliers are: $S_2 \succ S_1 \succ S_4 \succ S_5$. Obviously, S_2 is the optimum sustainable supplier.

[Insert Figure 2 about here]

5. Sensitivity analysis and managerial implications

5.1 Sensitivity analysis

DMs should presuppose parameter σ and threshold θ according to actual business conditions. The influences of these two coefficients on the final selection results of suppliers are analyzed, respectively, as follows.

On the one hand, when the threshold $\theta = 1.5$ is stable, the parameter σ changes. Supplier sorting under different values of parameter σ is given according to the step size of 0.2, as shown in Figure 3. It can be seen that the orders of S_1 and S_2 will not change with the change of parameters, but when σ is 0, 0.2, and 0.4, S_4 is better than S_5; when σ is 0.6, 0.8, and 1, S_4 and S_5 have the same ranking. In conclusion, the AQM is relatively insensitive to the parameter σ and the decision-making has good stability. When the value of σ is smaller, it indicates that the importance degree of no difference among alternatives has less influence on the final result.

[Insert Figure 3 about here]

On the other hand, when the parameter $\sigma = 0.5$ is stable, the threshold θ changes. Supplier sorting under different values of threshold θ is given according to the step size of 0.2 (shown in Figure 4). When θ is 1, 1.3, and 1.5, the decision results will not change. When θ is 1.7, S_1 and S_2 are in the same order as before, but S_4 and S_5 are in joint-third place. When θ is 1.9, S_1 and S_2 are in joint-first place, while S_4 and S_5 are in joint-third place. In summary, the AQM is relatively insensitive to threshold θ and decision-making has good stability. As the threshold value changes, the distinction of the final result is not significant, but the value of threshold value should not be greater than 1.94, otherwise the result will be meaningless.

[Insert Figure 4 about here]

When the parameter σ and threshold θ change simultaneously, the supplier ranking is given (shown as Figure 5). It can be seen that the ranking result is consistent with the ranking result obtained when the parameter is changed and the threshold is stable (shown as Figure 3). In short, the AQM is relatively insensitive to both parameter σ and threshold θ, but the change of threshold has a greater impact on the final decision-makings.

[Insert Figure 5 about here]

5.2 Comparative analysis

To illustrate the accuracy of the proposed model, this study also makes a comparative analysis with some existing methods, including the fuzzy TOPSIS, the fuzzy GRA, and the fuzzy VIKOR. Using the proposed model and the three comparative methods, the results are as shown in Table 14 and depicted in Figure 6 in a more intuitive way. We can see that S_2 is always the optimal supplier, which verifies the effectiveness of the method proposed in this study.

[Insert Table 14 and Figure 6 about here]

Additionally, there are some differences in the orders determined by the different methods. For instance, S_4 ranks higher than S_5 using the proposed model, while S_5 ranks higher than S_4 using the fuzzy TOPSIS. Besides, S_5 ranks higher than S_3 and S_3 ranks higher than S_4 when using the fuzzy GRA. It can also be seen that S_4 ranks higher than S_1 in the VIKOR method, while S_1 is more appropriate than S_4 from the result of the proposed model in this study. The explanations for the ranking inconsistences largely depend on the features of the different methods. The TOPSIS method solves the distance between each scheme and the positive and negative ideal solutions, before selecting the scheme closest to the positive ideal solution and furthest from the negative ideal solution as the best evaluation result. However, the correlation between the two ideal points is ignored. The GRA method calculates the gray relational degree of each scheme to the intuitionally fuzzy positive and negative ideal solution, before calculating the relative relational degree of the alternative scheme to the intuitionally fuzzy positive ideal solution. However, this method is still inadequate in the quantitative model of gray relational degree. The VIKOR method is characterized by considering the maximization of group benefits and the minimization of individual regrets for opposing views. In the process of using the VIKOR decision-making method, the value of the decision mechanism coefficient upsilon has a great influence on the final decision result, which will not guarantee the stability of the decision result.

It is expected that adopting the AQM will derive a more credible and reasonable ranking result to alternatives in solving SSS problems. First, there are different methods for depicting the precedence relationships between alternatives, among which, the directed graph and the 0-1 precedence relationship matrix are the most intuitive ones (Gou et al. 2016). Its calculation process is simple and the results can be derived in a short time. In particular, in the ultima directed graphs, different colors can be used to show different alternatives. Second, it is necessary to provide the specific evaluation information on alternatives with respect to different criteria and then construct the decision-making matrix. However, in lots of practical decision-making problems, it is difficult to construct such a decision-making matrix, and only the ranking of the alternatives can be given (Liu et al. 2019). The AQM was proposed to solve this kind of problem. Third, from the sensitivity analysis of the intuitionistic-fuzzy AQM, it can be seen that different decision-making results can be obtained by setting different parameters and thresholds, which indicates that adopting the AQM offers greater flexibility.

5.3 Managerial insights

The empirical illustration also indicates several important findings that contribute to a wider understanding of supply risk group decision-makings in SSS.

First of all, it is necessary for managerial decisions to be consistent with the corporate strategy for effective operations management (Govindan et al. 2017). From this perspective, the group decision-making procedure proposed in this study can build a consensus ranking of potential suppliers, while synthesizing viewpoints of different DMs. It can be seen from Table 5 that this study adopts group decision-making and uses intuitionistic fuzzy sets to determine the weights of DMs. After obtaining the DMs' weights, the decision-making matrix is aggregated and the entropy method is used to determine the weights of criteria objectively. It can be effectively used by managers and help to reduce the supply risk and uncertainty of choosing the most appropriate sustainable suppliers.

Second, the model proposed in this study can help enterprises establish a systematic framework for selecting the most appropriate sustainable supplier within a set of qualitative and quantitative criteria. According to the criteria weights calculated by the entropy weight method in Table 9, the weights of price risk and transportation cost risk are the highest. Meanwhile, in subsection 4.3, this study calculates the RPN weight corresponding to each criteria of each alternative supplier through FMEA and the criteria weights. According to the results in Table 13, it can be seen that S_3 has the highest RPN weight of transportation cost risk, which directly leads to the elimination of S_3. In conclusion, it is indicated that cost-related operational risk has the greatest impact on enterprise operation among supply risk. However, the impact of environmental and society-related risks on economy-related risks in supply risk should not be ignored.

Third, since the proposed model identifies suppliers for their level of supply risk through FMEA, it is intended to guide the suppliers with lower rankings to improve their performance under the most relevant factors. On the one hand, it is used to analyze suppliers that do not meet the requirements and reveal the right directions where they can improve. On the other hand, this model can improve the effectiveness of order allocation and reduce waste. Although S_3 is regarded as the worst supplier using the method adopted in this study, S_4 is regarded as the worst supplier using GRA. In this study, FMEA is used to directly filter out S_3, so that the order quantity will not be assigned to S_3 during the subsequent order allocation process. However, other methods cannot filter out S_3 directly and so there is high risk of assigning big orders to them.

Finally, most of managers will find acceptance in tools and models that can be easily understood. The AQM can be used to deal with hybrid fuzzy MCDM problems, in which the evaluation information of alternatives is represented by different kinds of fuzzy information. For example, this study applies the AQM to the decision-making matrix under the intuitionistic fuzzy information obtained in Table 8 and, finally, obtains the overall pros/overall cons/overall indifference weights for each alternative supplier in Table 12. This shows that the AQM can be adopted with intuitionistic fuzzy sets. In addition, the AQM can also be applied to cases where the evaluation information is the ranking of alternatives rather than the decision information. For the ranking information, the AQM has a relatively simple computation procedure and can obtain a robust ranking result based on both quantitative and qualitative criteria (Duan et al. 2019). In summary, in order to deal with the hybrid fuzzy information effectively, the AQM can flexibly manage the intricate MCDM problems with substantial numbers of criteria and alternatives.

6. Conclusions

Previous studies on SSS and supply risk mainly focused on the characteristics of supply chain, and most of them did not emphasize the supply risk from the perspectives of TBL (Wu et al. 2020). This study solves the risk-based SSS from the perspective of TBL, which extends the current literature on SSS to consider supply risk theoretically. Specifically, this research integrates intuitionistic fuzzy sets, the entropy weight method, and FMEA to identify high-risk suppliers and applies the AQM to rank the qualified suppliers concerning supply risk. The proposed model provides a flexible decision-making methodology for managers to select the suitable suppliers under a fuzzy environment in SSCs. In addition, an empirical illustration is given to verify the model' s applicability, while sensitivity analysis showing the stability and effectiveness of the proposed model.

The proposed model can identify the supply risk level of suppliers, analyze suppliers that do not meet the requirements, and reveal the right directions where they should improve. In addition, this model can also improve the effectiveness of order allocation and reduce risk-related costs. Whereas, this study helps enterprises to establish a good and in-depth partnership with suppliers, in order to, ultimately, reduce risks, ensure effective operations, and enhance the overall competitiveness of the SSCs.

There are three main advantages of the proposed model. Firstly, this study employs intuitionistic fuzzy set theory to deal with uncertain and inaccurate decision information in group decision-making, while the group decision-making procedure taking DMs weights into account. It can not only help to reduce the pure subjectivity of decision-making, but also makes the final ranking results more reasonable. Secondly, this study adopts the improved FMEA, and combines the criteria weights with the final calculation results, so it can more effectively predict the risk of potential suppliers. Finally, this study combines the advantages of AQM into SSS, which can intuitively generate the ranking of alternative suppliers and enhance the efficiency of supplier decision. Therefore, the good implementation of the proposed model can lead to better decisions-makings and improve the competitiveness.

At the same time, there are several shortcomings in this research, as well as interesting potential directions for future research. First, it is impractical to incorporate too many dimensions of supply risk in a single research study. The impacts of disruptive risks, such as natural disruptive events (low-frequency but high-impact disruptive events) and their impacts on suppliers and manufacturing can be investigated in future research. Furthermore, the proposed model might also be applicable to other similar supplier selection problems. The AQM can be combined with other methods to deal with complex multi-objective decision model problems with a large number of criteria and alternatives, in order to deal with the hybrid fuzzy information in the decision process effectively. Also, this study does not consider order allocation and does not establish a mathematical model, so this may also be an area worthy of further research.

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Tables

Table 1: The comparison of existing methods with this research in supplier selection

Author(s)	Decision-making environment	Risk	Sustainability			Method	Application	Features
			Eco	Soc	Env			
Wu et al. (2012)	Uncertain	√	√	√		Multiple objective programming	No specific	Construct a fuzzy multi-objective programming model for supplier selection while taking risk factors into consideration.
Azadi et al. (2015)	Uncertain		√	√	√	DEA	Chemical industry	Propose an integrated DEA enhanced Russell measure (ERM) model in fuzzy context to select the best sustainable suppliers.
Hosseini and Barker (2016)	Certain	√	√		√	Bayesian network	No specific	Extend a Bayesian network formulation for supplier selection accounting for operational and disruption risks.
Chen et al. (2017)	Certain		√			Conceptual model	Retail industry	Develop a stylized two-player model framework to study the mutual dependence of the supply chain partners.
Banaeian et al. (2018)	Uncertain		√	√	√	TOPSIS+VIKOR+GRA	Food industry	Provide a comparison between the performance of TOPSIS, VIKOR, and GRA.
Kannan (2018)	Uncertain		√	√	√	ISM+ANP+COPRAS-G	Textile industry	Employ a decision-making framework based on the CSF theory with fuzzy Delphi, Interpretive Structural Modelling (ISM), ANP, and COPRAS-G.
Pishchulov et al. (2019)	Certain		√	√	√	AHP	Construction industry	Develop a revised AHP method that overcomes criticism of DEA-based preference aggregation procedure.
Pang et al. (2020)	Uncertain	√	√			Three-way decisions models	E-commerce industry	Establish a data-driven method based on the idea of multi-granulation and three-way decisions under intuitionistic uncertain linguistic environment.
The proposed model	Uncertain	√	√	√	√	Entropy weight method + FMEA + AQM	Manufacturing industry	Integrate Entropy weight method and FMEA for identifying qualified suppliers, and apply AQM for ranking the suppliers concerning supply risks.

Table 2: Linguistic terms for ranking the importance of the DMs and criteria

Linguistic variables	IFNS
Very important (VI)	(0.90,0.10)
important (I)	(0.75,0.20)
medium (M)	(0.50,0.45)
unimportant (U)	(0.35,0.60)
Very unimportant (VU)	(0.10,0.90)

Table 3: General evaluation scheme of FMEA

Rank	Likelihood	Severity	Detection
9-10	Very high and inevitable (due to new designs)	Failure to meet safety and/or regulatory requirements	No detection opportunity
7-8	High and uncertain (due to operating conditions)	Loss or degradation of primary function	Possibly detected by offline testing
5-6	Moderate (with information of similar designs and simulation data)	Loss or degradation of secondary function	Possibly detected by online planned testing
3-4	Low (no observed failures with almost identical designs)	Annoying effects	Possibly detected by online automatic continuous testing
1-2	Very low	No discernible effects	Highly noticeable in regular operations

Table 4: Selected criteria for sustainable supplier selection

Dimension	Criteria	Reference
Economic	Price risk (C_1)	Tang and Musa (2011)
	Quality risk (C_2)	Tummala and Schoenherr (2011)
	Transportation cost risk (C_3)	Wu and Barnes (2018)
	On time delivery risk (C_4)	Fang et al. (2016)
Social	Employee management risk (C_5)	Cheraghalipour and Farsad (2018)
	Work safety risk (C_6)	Azadnia et al. (2015)
	Complaint processing risk (C_7)	Chen and Wu (2013)
	Enterprise reputation risk (C_8)	Sodhi et al. (2012)
Environmental	Green environmental protection materials risk (C_9)	Gupta and Barua (2017)
	Pollution control initiatives risk (C_{10})	Awasthi et al. (2010)
	Recycling risk (C_{11})	Foroozesh et al. (2019)

Table 5: The importance of DMs and their corresponding weights

	DM_1	DM_2	DM_3
Linguistic Terms	Very High	Very High	Medium
Weight	0.387	0.387	0.226

Table 6: Linguistic decision-making matrix of potential suppliers

Criteria	DM$_1$					DM$_2$					DM$_3$				
	S_1	S_2	S_3	S_4	S_5	S_1	S_2	S_3	S_4	S_5	S_1	S_2	S_3	S_4	S_5
C_1	VL	VH	VH	M	M	L	M	H	H	H	L	H	VH	H	H
C_2	VH	M	VL	L	L	L	M	M	M	M	M	M	L	L	L
C_3	M	VH	VL	H	M	VH	VH	VL	L	L	H	VH	VL	M	M
C_4	H	VH	L	M	H	VL	L	VH	M	M	L	M	M	M	M
C_5	VH	L	M	M	M	VL	M	H	M	M	M	L	M	M	M
C_6	M	M	M	M	M	L	VL	L	L	L	L	L	L	L	L
C_7	VH	H	VL	H	H	L	M	M	M	M	M	M	L	M	M
C_8	VH	M	L	H	H	VL	L	M	VL	L	M	L	L	L	M
C_9	VH	H	H	H	H	VL	L	L	L	L	M	M	M	M	M
C_{10}	VH	M	M	M	M	L	L	L	L	L	M	L	L	L	L
C_{11}	VH	M	M	M	M	VL	L	L	L	L	M	L	L	L	L

Table 7: The intuitionistic fuzzy decision-making matrix

Criteria	DM_1					DM_2					DM_3				
	S_1	S_2	S_3	S_4	S_5	S_1	S_2	S_3	S_4	S_5	S_1	S_2	S_3	S_4	S_5
C_1	(0.10,0.90)	(0.90,0.10)	(0.90,0.10)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.50,0.45)	(0.75,0.20)	(0.75,0.20)	(0.75,0.20)	(0.35,0.60)	(0.75,0.20)	(0.90,0.10)	(0.75,0.20)	(0.75,0.20)
C_2	(0.90,0.10)	(0.50,0.45)	(0.10,0.90)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)
C_3	(0.50,0.45)	(0.90,0.10)	(0.10,0.90)	(0.75,0.20)	(0.50,0.45)	(0.90,0.10)	(0.90,0.10)	(0.10,0.90)	(0.35,0.60)	(0.35,0.60)	(0.75,0.20)	(0.90,0.10)	(0.10,0.90)	(0.50,0.45)	(0.50,0.45)
C_4	(0.75,0.20)	(0.90,0.10)	(0.35,0.60)	(0.50,0.45)	(0.75,0.20)	(0.10,0.90)	(0.35,0.60)	(0.90,0.10)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)
C_5	(0.90,0.10)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.10,0.90)	(0.50,0.45)	(0.75,0.20)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)
C_6	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.10,0.90)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)
C_7	(0.90,0.10)	(0.75,0.20)	(0.10,0.90)	(0.75,0.20)	(0.75,0.20)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)
C_8	(0.90,0.10)	(0.50,0.45)	(0.35,0.60)	(0.75,0.20)	(0.75,0.20)	(0.10,0.90)	(0.35,0.60)	(0.50,0.45)	(0.10,0.90)	(0.35,0.60)	(0.50,0.45)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.50,0.45)
C_9	(0.90,0.10)	(0.75,0.20)	(0.75,0.20)	(0.75,0.20)	(0.75,0.20)	(0.10,0.90)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)
C_{10}	(0.90,0.10)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.50,0.45)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)
C_{11}	(0.90,0.10)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.50,0.45)	(0.10,0.90)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.50,0.45)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)	(0.35,0.60)

Table 8: The aggregated intuitionistic fuzzy decision-making matrix

Criteria	Suppliers				
	S_1	S_2	S_3	S_4	S_5
C_1	(0.263,0.702,0.035)	(0.771,0.209,0.020)	(0.857,0.131,0.012)	(0.673,0.274,0.053)	(0.673,0.274,0.053)
C_2	(0.703,0.281,0.016)	(0.500,0.450,0.050)	(0.334,0.628,0.038)	(0.413,0.537,0.050)	(0.413,0.537,0.050)
C_3	(0.771,0.209,0.020)	(0.900,0.100,0.000)	(0.100,0.900,0.000)	(0.577,0.368,0.056)	(0.447,0.503,0.050)
C_4	(0.491,0.459,0.051)	(0.703,0.281,0.016)	(0.703,0.281,0.016)	(0.500,0.450,0.050)	(0.618,0.329,0.054)
C_5	(0.663,0.329,0.008)	(0.413,0.537,0.050)	(0.618,0.329,0.054)	(0.500,0.450,0.050)	(0.500,0.450,0.050)
C_6	(0.413,0.537,0.050)	(0.334,0.628,0.038)	(0.413,0.537,0.050)	(0.413,0.537,0.050)	(0.413,0.537,0.050)
C_7	(0.703,0.281,0.016)	(0.618,0.329,0.054)	(0.334,0.628,0.038)	(0.618,0.329,0.054)	(0.618,0.329,0.054)
C_8	(0.663,0.329,0.008)	(0.413,0.537,0.050)	(0.413,0.537,0.050)	(0.491,0.459,0.051)	(0.577,0.368,0.056)
C_9	(0.663,0.329,0.008)	(0.577,0.368,0.056)	(0.577,0.368,0.056)	(0.577,0.368,0.056)	(0.577,0.368,0.056)
C_{10}	(0.703,0.281,0.016)	(0.413,0.537,0.050)	(0.413,0.537,0.050)	(0.413,0.537,0.050)	(0.413,0.537,0.050)
C_{11}	(0.663,0.329,0.008)	(0.413,0.537,0.050)	(0.413,0.537,0.050)	(0.413,0.537,0.050)	(0.413,0.537,0.050)

Table 9: Calculated intuitionistic fuzzy entropy values and the weights of criteria

Weights	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}
E_j	0.784	0.955	0.731	0.933	0.967	0.977	0.921	0.972	0.956	0.964	0.974
w_j	0.249	0.052	0.311	0.078	0.038	0.026	0.091	0.033	0.050	0.042	0.030

Table 10: Risk assessment of potential suppliers

Criteria	Risk assessment														
	S_1			S_2			S_3			S_4			S_5		
	L	S	D	L	S	D	L	S	D	L	S	D	L	S	D
C_1	3	5	5	2	2	2	2	2	2	3	3	3	2	2	2
C_2	2	2	4	4	3	4	5	5	5	2	3	2	3	3	2
C_3	2	2	3	2	2	3	6	5	6	3	2	2	4	4	4
C_4	3	3	4	2	2	2	6	6	6	3	3	3	3	2	2
C_5	2	2	2	3	3	3	4	4	4	4	3	3	3	3	3
C_6	2	2	2	3	3	3	4	3	3	3	3	3	3	3	3
C_7	3	3	3	2	2	2	6	6	6	3	3	3	3	3	3
C_8	2	3	3	3	2	3	4	4	4	3	3	2	3	3	3
C_9	2	2	2	3	3	3	4	4	4	3	4	2	4	4	4
C_{10}	3	3	3	3	3	3	4	5	5	3	3	3	3	3	4
C_{11}	4	2	3	4	4	4	5	5	5	4	3	3	4	4	4

Table 11: Weighted RPNs of S_3

Criteria	Risk assessment				Criterion's weight (w_j)	Weighted RPN (R_j)
	L	S	D	RPN		
C_1	2	2	2	0.89	0.25	0.22
C_2	5	5	5	22.58	0.05	1.18
C_3	6	5	6	31.15	0.31	9.68
C_4	6	6	6	37.24	0.08	2.90
C_5	4	4	4	11.42	0.04	0.43
C_6	4	3	3	6.42	0.03	0.17
C_7	6	6	6	37.24	0.09	3.40
C_8	4	4	4	11.42	0.03	0.37
C_9	4	4	4	11.42	0.05	0.57
C_{10}	4	5	5	17.67	0.04	0.74
C_{11}	5	5	5	22.58	0.03	0.68
Total						20.34
Average						1.85

Table 12: Overall weights for each pair of potential suppliers

Overall weights		Values
Overall pros weights	$w(S_1 \square S_2)$	0.362
	$w(S_1 \square S_4)$	0.647
	$w(S_1 \square S_5)$	0.647
	$w(S_2 \square S_4)$	0.690
	$w(S_2 \square S_5)$	0.690
	$w(S_4 \square S_5)$	0.311
Overall cons weights	$w(S_1 \square S_2)$	0.638
	$w(S_1 \square S_4)$	0.327
	$w(S_1 \square S_5)$	0.327
	$w(S_2 \square S_4)$	0.096
	$w(S_2 \square S_5)$	0.096
	$w(S_4 \square S_5)$	0.110
Overall indifference weights	$w(S_1 \approx S_4)$	0.026
	$w(S_1 \approx S_5)$	0.026
	$w(S_2 \approx S_4)$	0.214
	$w(S_2 \approx S_5)$	0.214
	$w(S_4 \approx S_5)$	0.579

Table 13: Overall pros and cons indicated values among potential suppliers

Suppliers	S_1	S_2	S_4	S_5
S_1	-	0.568	1.940	1.940
S_2	1.762	-	3.924	3.924
S_4	0.515	0.255	-	1.501
S_5	0.515	0.255	0.666	-

Table 14: Results of sensitivity analysis for different methods

Suppliers	TOPSIS		GRA		VIKOR		FMEA+AQM	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank
S_1	0.626	2	0.524	2	0.498	3	1	2
S_2	0.700	1	0.558	1	0.000	1	3	1
S_3	0.384	5	0.463	4	1.000	5	-	5
S_4	0.513	4	0.454	5	0.425	2	-1	3
S_5	0.520	3	0.515	3	0.514	4	-3	4

Figures

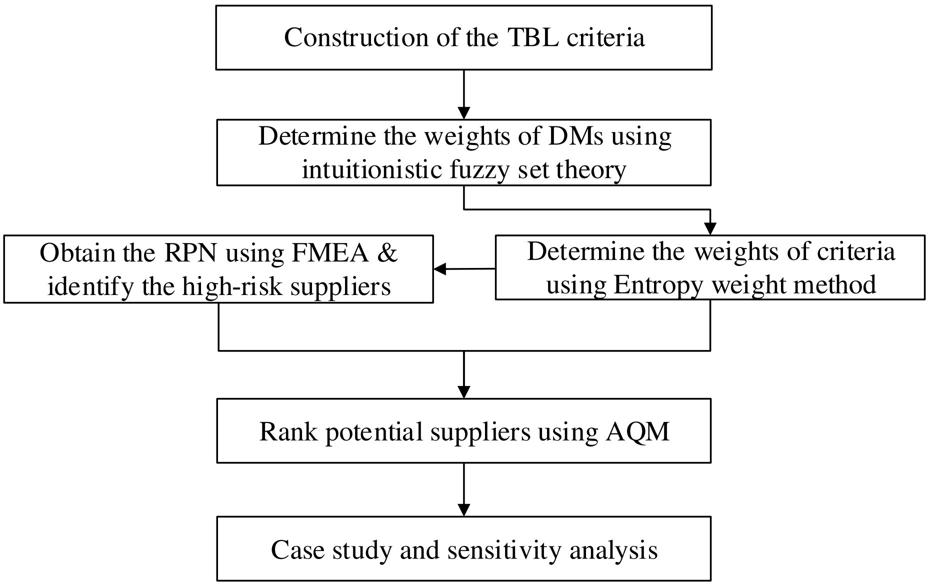

Figure 1: The proposed framework for risk-based sustainable supplier selection

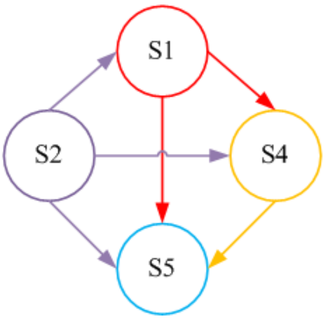

Figure 2: Directed graph for the potential suppliers

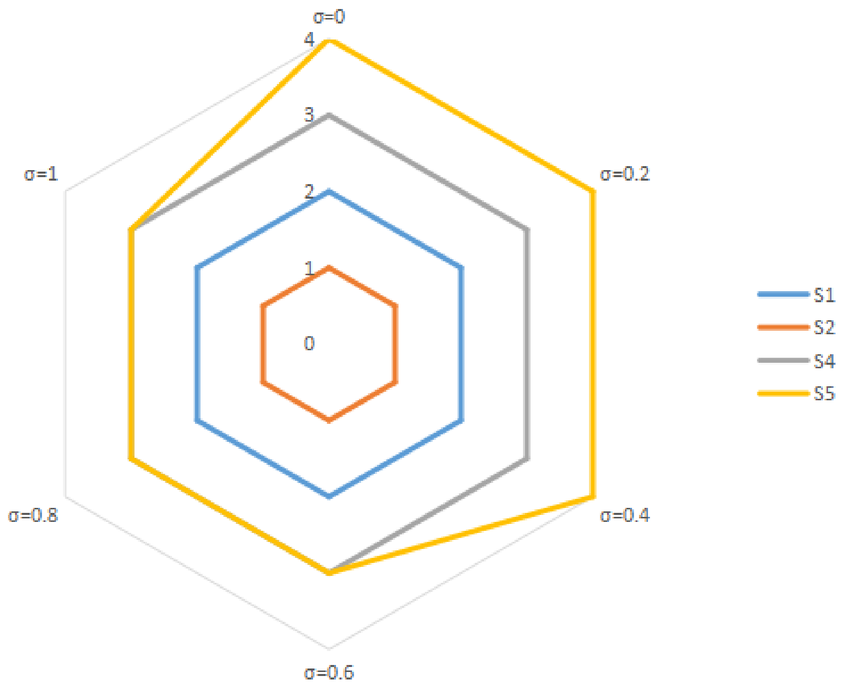

Figure 3: Supplier rankings as parameter σ changes

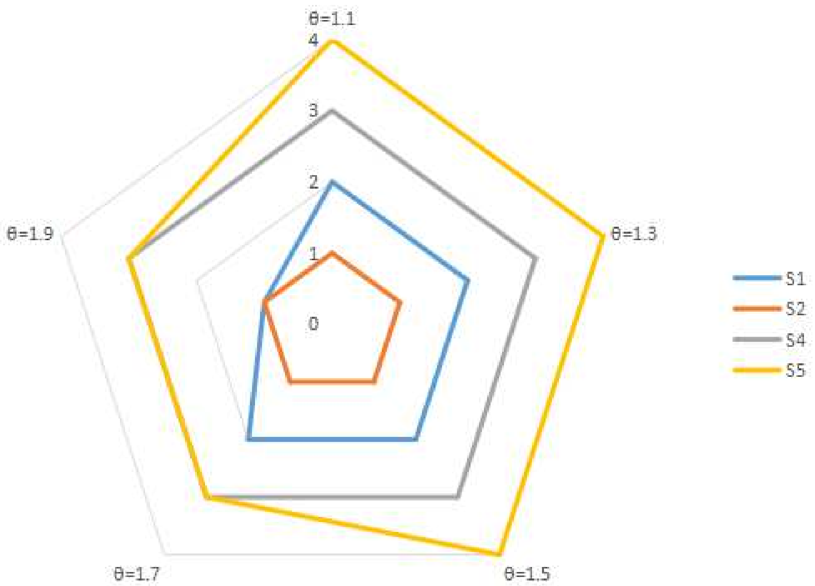

Figure 4: Supplier rankings as threshold θ changes

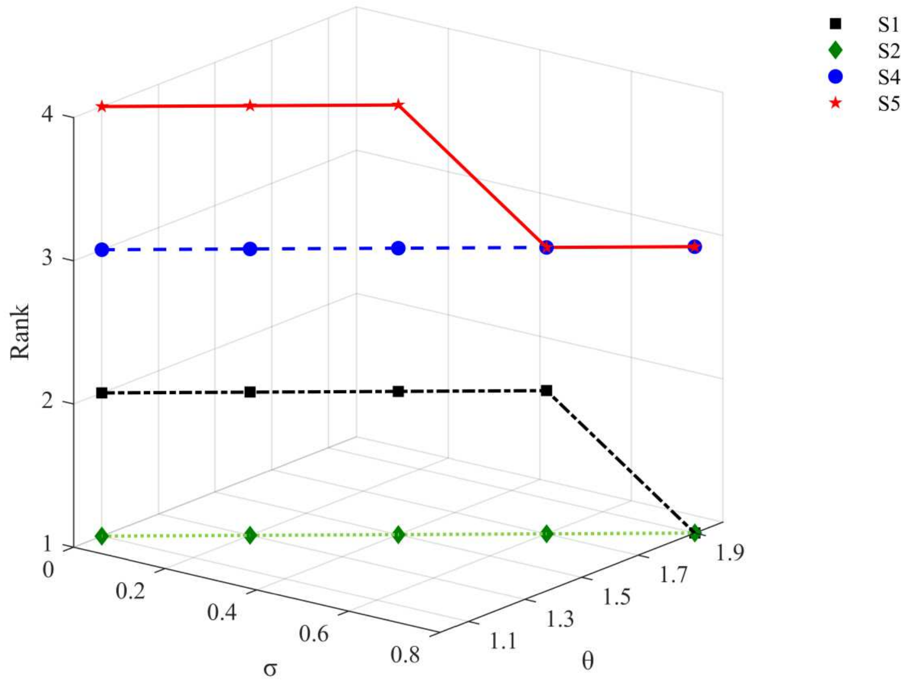

Figure 5: Supplier rankings as parameter σ and threshold θ changes simultaneously

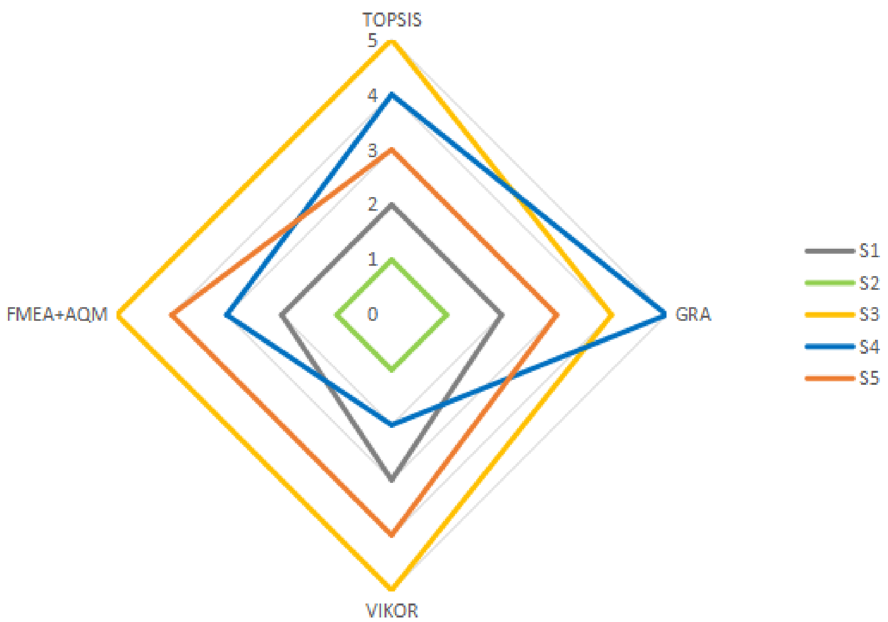

Figure 6: Results of sensitivity analysis of different methods

Figures

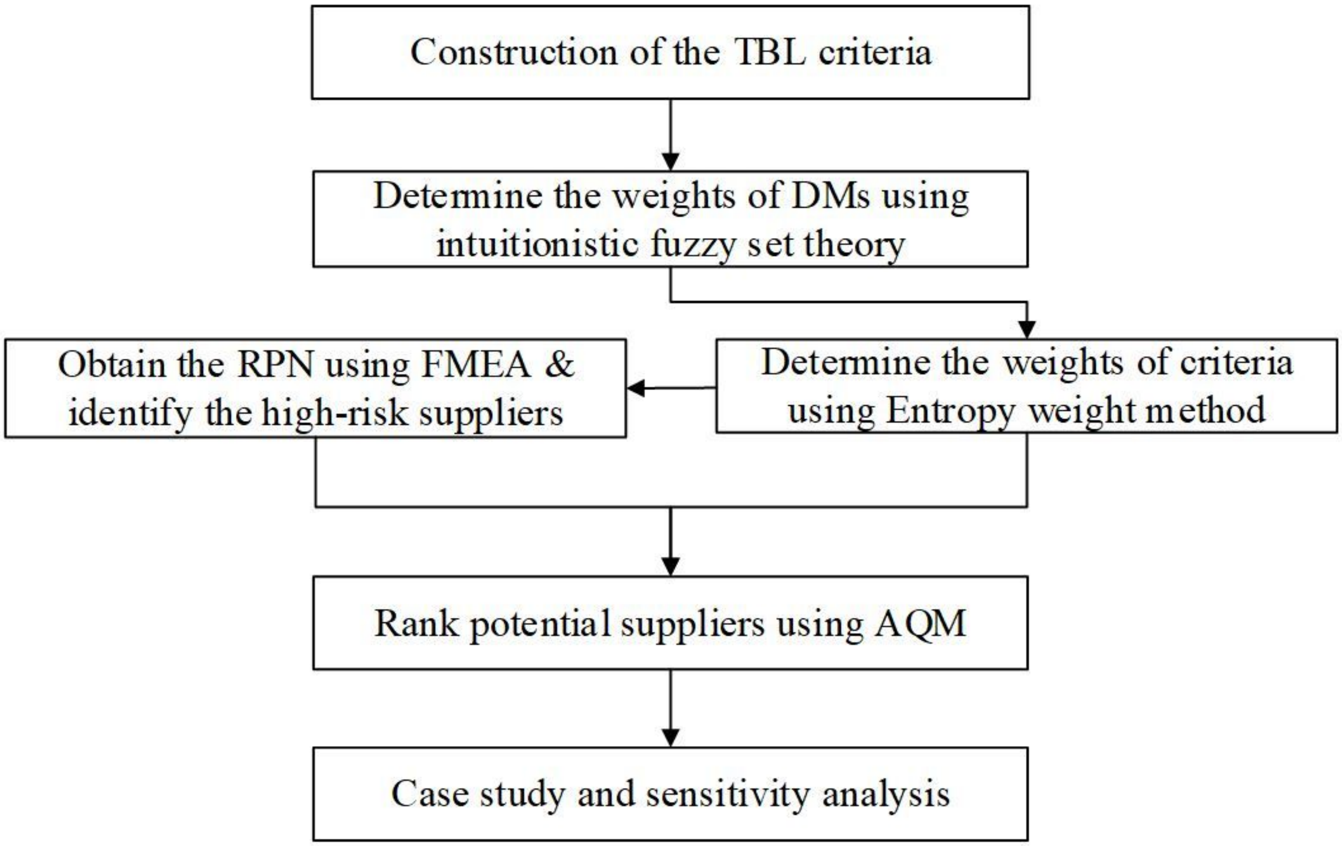

Figure 1

The proposed framework for risk-based sustainable supplier selection

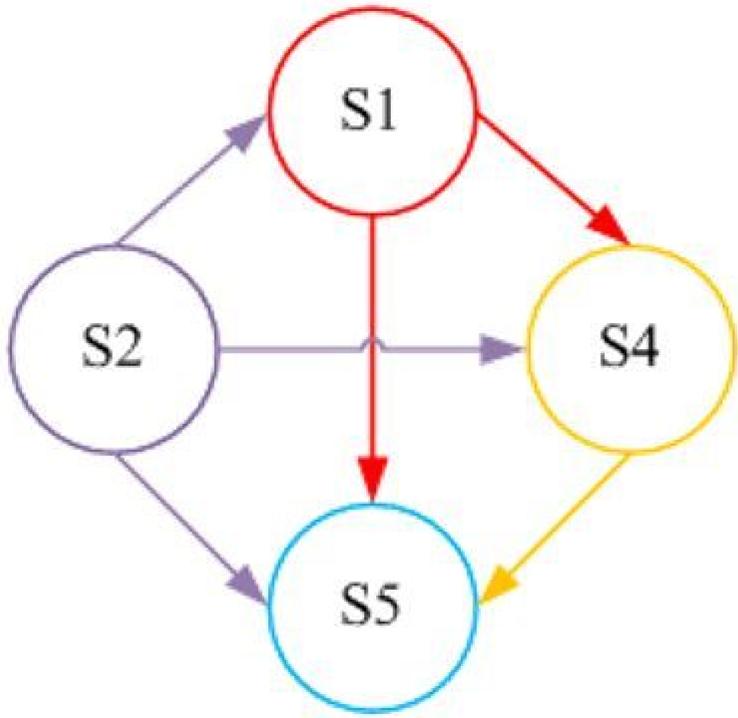

Figure 2

Directed graph for the potential suppliers

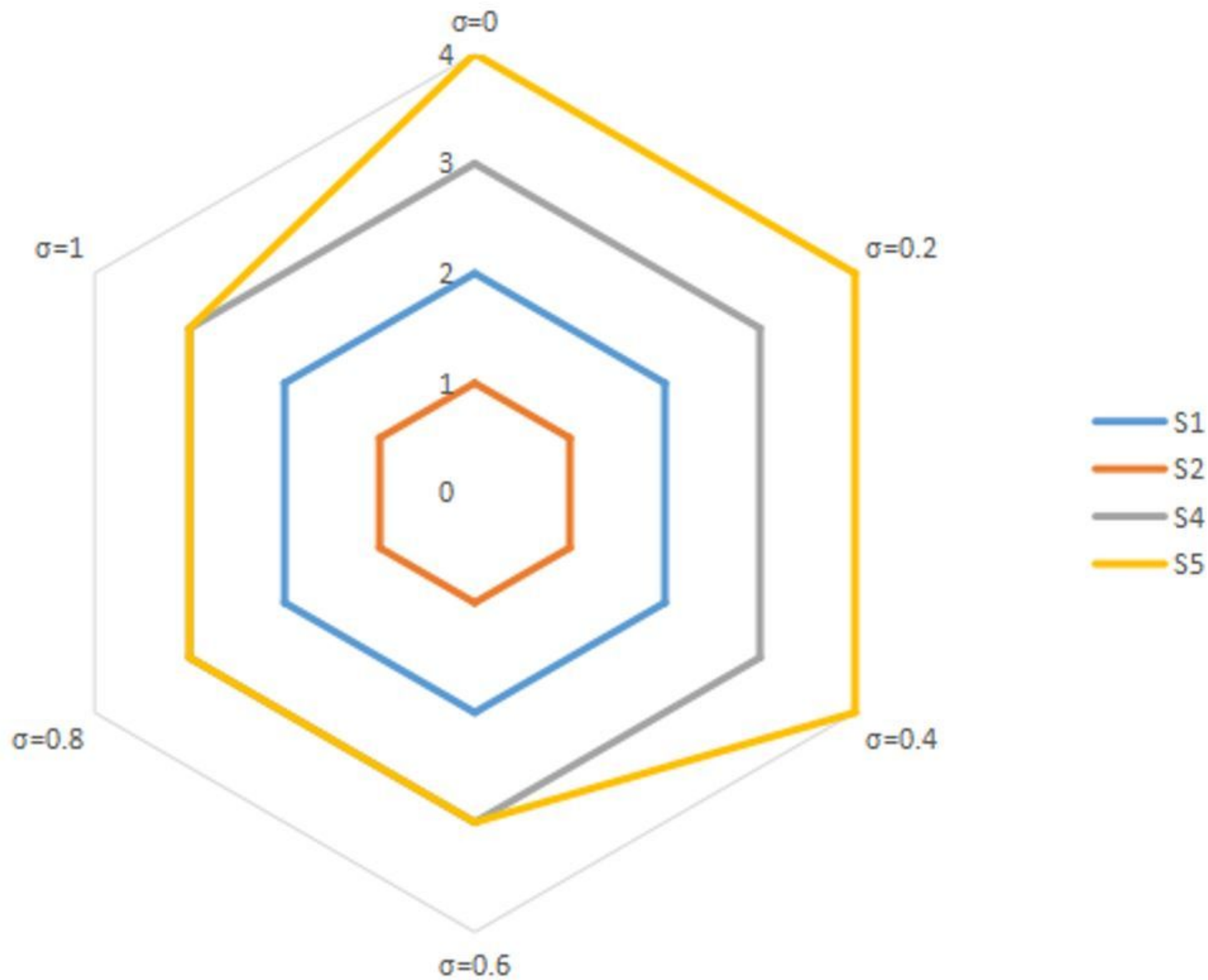

Figure 3

Supplier rankings as parameter σ changes

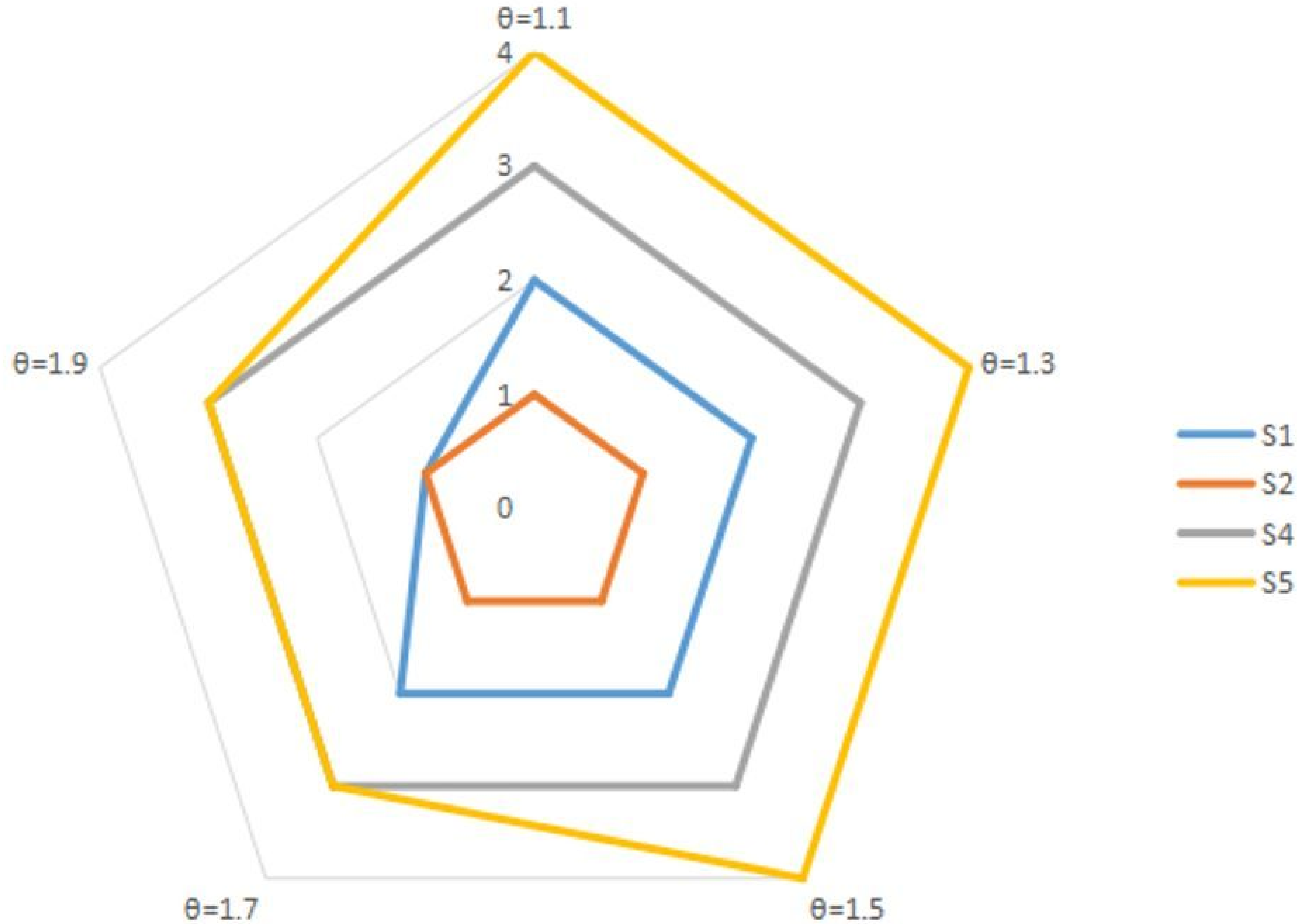

Figure 4

Supplier rankings as threshold θ changes

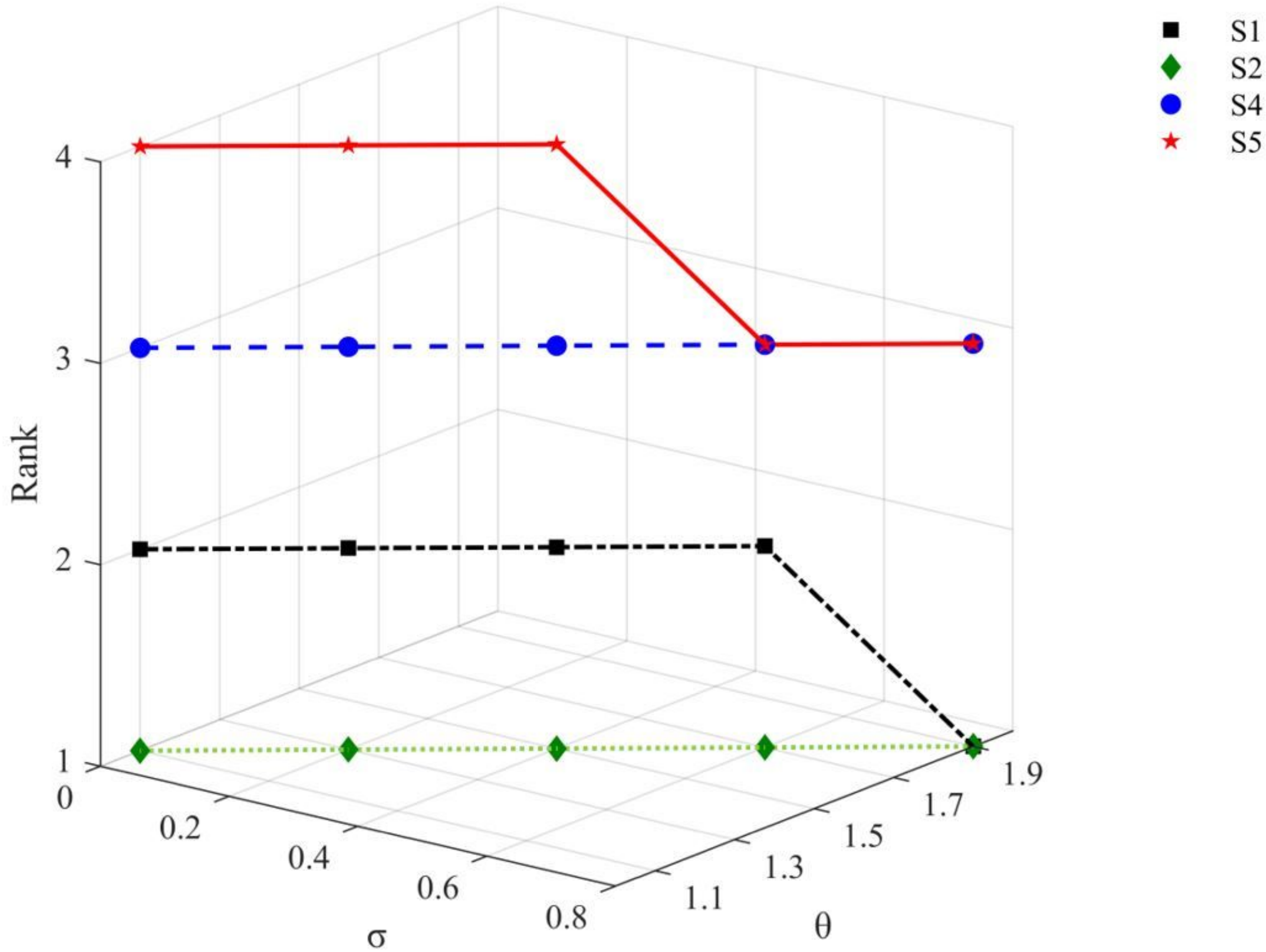

Figure 5

Supplier rankings as parameter σ and threshold θ changes simultaneously

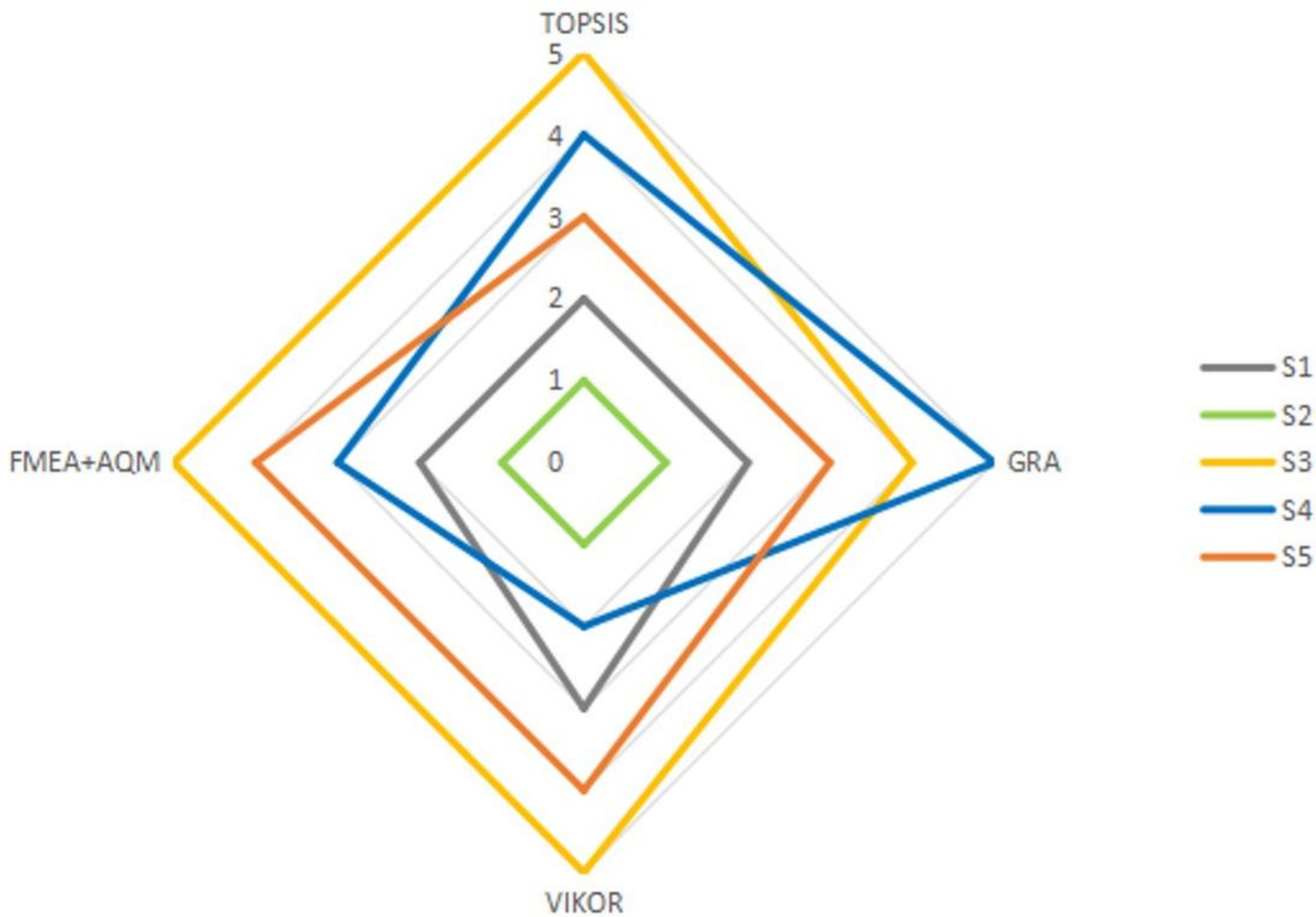

Figure 6

Results of sensitivity analysis of different methods