



Supplier selection to support environmental sustainability: the stratified BWM TOPSIS method

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Abstract

Organisations need to develop long-term strategies to ensure they incorporate innovation for environmental sustainability (IES) to remain competitive in the market. This can be challenging given the high level of uncertainty regarding the future (e.g., following the COVID pandemic). Supplier selection is an important decision that organisations make and can be designed to support IES. While the literature provides various criteria in the field of IES strategies, it does not identify the criteria which can be utilised to assist organisations in their supplier selection decisions. Moreover, the literature in this field does not consider uncertainty related to the occurrence of possible future events which may influence the importance of these criteria. To address this gap, this paper develops a novel criteria decision framework to assist supplier evaluation in organisations, taking into consideration different events that may occur in the future. The framework that combines three decision-making methods: the stratified multi-criteria decision-making method, best worst method, and technique for order of preference by similarity to ideal solution. The framework, proposed in this paper, can also be adopted to enable effective and sustainable decision making under uncertainty in various fields.

Keywords Supplier evaluation · Environmental sustainability innovation · MCDM · SMCDM

1 Introduction

To remain competitive in the market, innovation for sustainability is becoming an integral part of organisations (Bohnsack et al., 2020; Elabed et al., 2021). This type of innovation

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is explained as the consideration of three sustainability dimensions (economic, social, and environmental) in procuring new processes, technologies, and materials to produce goods or services (Bui et al., 2020; Gupta et al., 2020; Rathore & Sarmah, 2020).

Of these three dimensions, environmental sustainability plays a pivotal role in achieving sustainable development (Boons et al., 2013). This dimension of sustainability is becoming a prerequisite for organisations given the negative impacts of industrialisation on human life alongside the pressure from environmental activists (Gupta et al., 2020). Moreover, governments will enforce stricter regulations in response to environmental concerns (see e.g., the recent UN Climate Change Conference (COP26) in Glasgow on 31 October–13 November 2021¹). To enhance the effective utilisation of natural resources and reduce the carbon footprint, companies need to adopt innovation for environmental sustainability (IES) (Ahmadi et al., 2020). IES can be described as both product and process innovation and consists of employing efficient innovative solutions to a variety of environmental issues, altering the status quo, and improving social norms (Tidd & Bessant, 2018).

While the literature on IES is expanding, there is insufficient research on the development of a supplier selection framework that supports the achievement of IES goals. Supplier selection is an important decision, with long-lasting impacts on the performance of the organisation (Chen et al., 2020). As the literature in the field of IES does not provide a supplier selection framework, there is no clarity on which criteria should be utilised by organisations in their supplier selection processes (to be aligned with their IES goals). This paper addresses this gap by reviewing the literature and extracting key criteria in the field of IES, which can potentially support the development of a criteria decision framework for supplier selection. The extracted criteria are then utilised to develop a supplier selection framework.

The proposed framework is also capable of considering uncertainty related to the occurrence of likely events—events which may occur in the future and impact the weightings of the extracted decision criteria. While the literature provides supplier selection frameworks that consider uncertainty (Ecer & Pamucar, 2020), the type of uncertainty they consider is commonly related to occasions where the decision maker utilises linguistic variables or provides fuzzy numbers for the selection criteria (or the scores assigned to potential suppliers). This paper addresses this gap by providing a decision framework that considers likely events through a stratified-based approach. The developed framework utilises three decision-making methods, namely the stratified multi-criteria decision-making (SMCDM) method (Asadabadi, 2018), the best worst method (BWM) (Rezaei, 2015), and the technique for order of preference by similarity to ideal solution (TOPSIS) (Lai et al., 1994).

Therefore, this paper contributes to the literature by identifying the decision criteria which is required for the development of IES supplier selection frameworks. The paper also contributes to the literature methodologically. It develops a novel decision-making framework that combines the aforementioned three methods, for the first time, which can be used to address a range of MCDM problems in uncertain environments. In this framework, (1) the SMCDM method is used to integrate uncertainty related to the occurrence of several events (which impact the weightings of the selection criteria), (2) BWM is used to compute the weightings of the criteria under the occurrence of each of the events (or multiple events), and (3) TOPSIS is used to facilitate the process of assigning scores on suppliers and finding their optimal ranking. The proposed criteria decision-making framework is the first to examine the capabilities of the SMCDM method to work in combination with BWM and TOPSIS (the framework is labelled S-BWM-TOPSIS).

¹ <https://unfccc.int/>.

This article is organised as follows. Section 2 provides a review of the most related literature. The research methodology is presented in Sect. 3 and illustrated in Sect. 4. Comparative analysis is presented in Sect. 5. Section 6 presents Discussion. Finally, the conclusion and suggestions for future works are provided in Sect. 7.

2 Literature review

A review of the literature is submitted in this section. Firstly, the reasons to consider sustainability criteria in supply chain decisions are explained. Then, the previous studies on innovation for environmental sustainability are reviewed (to extract IES criteria). Finally, why it is important to consider uncertainty related to the occurrence of future events is clarified.

2.1 Sustainability criteria and the supplier selection problem

The key advantage of sustainable supply chain management (SSCM) over traditional approaches is that SSCM requires executives and decision makers to pay particular attention to social, economic and environmental factors while managing supply chains (Fahimnia et al., 2017; Ortiz-Barrios et al., 2020). The literature also defines SSCM as a supply chain planning strategy that takes into account socio-economic and environmental development simultaneously (Ahi & Searcy, 2013; Ali et al., 2020). Regardless of how SSCM is defined, the consideration of sustainability criteria significantly enhances the performance of corporations' supply chains. These criteria may also help organisations achieve a competitive advantage and enhance their reputation (Ahmadi et al., 2020). This further helps manufacturing corporations achieve their sustainable development goals (Esfahbodi et al., 2016) and contributes to improving corporation effectiveness (Vargas et al., 2018). The pressures coming from society and regulations from governments contribute to increasing the speed at which organisations adopt sustainability criteria in various aspects of their performance (Ecer & Pamucar, 2020). Companies are now expected to handle their responsibilities related to social, economic, and environmental issues to manage sustainability initiatives. Moreover, research shows employing sustainability criteria may also considerably improve the performance of the supply chain (Bui et al., 2020; Chardine-Baumann & Botta-Genoulaz, 2014).

A key decision every organisation makes is to select the right supplier (Ahmadi et al., 2020). This may have long impacts on the performance of the organisation and influence the organisation's sustainability (Azadnia et al., 2015). Many organisations find sustainable supplier selection as an important way to show their customers that they are willing to move towards a sustainable future while also remaining competitive in the market. With the increased popularity of the concept of sustainability, researchers have exposed the significance of incorporating sustainability criteria in traditional supplier selection processes (Bai et al., 2021; Kusi-Sarpong et al., 2019). Research shows incorporating environmental and social criteria into conventional supplier selection considerably contributes to the development of sustainable supplier evaluation and selection processes (Chen et al., 2020). The exponential growth of research papers in this field may also be considered as an indication of its significance to researchers and its popularity to practitioners.

Aligned with research in the field of sustainability, this paper also develops a sustainable supplier selection framework. However, the proposed framework introduces a new typology by focusing on enhancing the environmental aspect of sustainability innovation in the supplier

selection process. The environmental criteria of sustainability innovation are explained in the next sub-section.

2.2 Environmental criteria of sustainability innovation

To achieve sustainable development, innovation for sustainability is a prerequisite (Silva et al., 2019). One of the key reasons why organisations create innovation is to ensure sustainable growth in the market (Koberg & Longoni, 2019). Sustainable innovation is defined as continuous improvement in products, services, or processes, with the aim of diminishing negative socio-environmental impacts (Beise & Rennings, 2005). To implement sustainability innovation in organisations, the following three dimensions need to be considered: social, economic, and environmental (Gupta et al., 2020).

Innovation for environmental sustainability (IES) includes innovations in products, services, and processes that utilise innovative technologies and strategies to save energy and reduce pollution and undesirable by-products (Chen et al., 2020; Gupta et al., 2020). These innovations may promote the greener production of goods and may ultimately resolve many environmental concerns. Environmental innovation is essential for enhancing the socio-environmental and financial outcomes of companies (Ma et al., 2020).

A review of the previous studies reveals that the discussion of a decision framework for supplier selection which considers IES is missing from the literature. Given this, it is not clear which criteria should be considered to support the selection of a supplier that is aligned with IES goals. Therefore, we have conducted a review of the literature in the field of IES and extracted the most important criteria that have the potential to be used as criteria for supplier selection. The list of these criteria, extracted from the literature, which is provided in Table 1 can be utilised as a guideline for IES supplier selection. Managers and decision makers can refer to this list and see which criteria from this list can be used in their supplier selection process. They may remove, add, or modify these criteria based on what they think is the best for their case of supplier selection. In our case study, in Sect. 4.2, we have provided decision makers with these criteria. They were given the option of selecting some of these, modifying them, and removing the ones that do not fit their strategies (in our case study, they selected five of them as presented in Sect. 4.2). A summary of our review is presented in Table 1.

In summary, supplier selection is a multi-criteria decision-making problem. The decision criteria can be chosen to promote the selection of the supplier that is the best to support the achievement of IES goals. While IES is a growing field of research, there are insufficient studies on the development of IES supplier selection frameworks. This limits the ability of organisations to identify IES criteria to support the development of a decision framework for their supplier selection processes. This paper addresses this gap by providing a summary of key criteria in the field of IES. These extracted IES criteria are used in our study to further develop an innovative decision framework for supplier selection which also handles uncertainty.

2.3 Uncertainty and future events

This paper considers uncertainty related to the occurrence of future events by utilising the SMCDM method. The SMCDM method is relatively new to the literature (only a few years past its original proposal by Asadabadi (2018)). The method is based on the concept of stratification (CST), which was introduced to the literature by Zadeh (2016). CST describes a system that receives inputs, based on which it transitions from one state to another (Asadabadi

Table 1 IES criteria extracted from the literature

Criteria	Description	Authors
Employing a variety of initiatives for carbon reduction	This refers to using various initiatives to decrease carbon usage	Borsatto and Amui (2019), Todeschini et al. (2020)
Developing environmentally sustainable production	This refers to implementing innovative methods in the production for decreasing waste and environmental issues in manufacturing	Carter et al. (2019), Ma et al. (2020)
Commitment to issues related to the environment	This refers to utilizing and implementing various environmental standards in corporations	Borsatto and Amui (2019), Silva et al. (2019)
Application of policies related to the environment as well as demands in the market	This refers to implementing environmental management programs for manufacturing environmentally friendly products	Carter et al. (2019), Ahmadi et al. (2021)
Investing in the environment to make an economic gain	This refers to investing in the issues related to environmental programs and economic achievement	Sala et al. (2020), Silvestre and Țircă (2019)
Resource accessibility as well as green competencies	This refers to implementing effective strategies to ensure access to resources	Koberg and Longoni (2019), Gupta et al. (2020)
Collaborating with rivals, and groups related to the environment	This refers to cooperating with diverse environmental groups, with the goal of producing environmentally sustainable products	Mousavi and Bossink (2020), Sala et al. (2020)
Product design considering factors such as reusing and being energy efficient	This refers to taking into consideration reusing and being energy efficient in the product design stage	Todeschini et al. (2020), Gupta et al. (2020)
Factors related to environmental planning in organizations	This refers to employing environmental planning-related standards in the firms	Ma et al. (2020), Silva et al. (2019)
Rules and codes relevant to environmental issues	This refers to considering regulations related to the environmental problems	Koberg and Longoni (2019), Mousavi and Bossink (2020)

et al., 2018). States are placed in a range of strata to facilitate the analysis of its transitions from one stratum to another (Zadeh, 2016). Asadabadi adopted the fundamentals of CST, such as system (transformed to decision), states (scenarios), inputs (events), outputs (criteria weightings), and developed the SMCDM method. The performance of SMCDM has already been examined in areas such as supplier selection (Asadabadi, 2018), project management (Asadabadi & Zwikael, 2021), and waste management (Torkayesh et al., 2021). Despite the earlier applications of the SMCDM method, prior to this study, it had not yet been utilised in

combination with BWM and TOPSIS, nor had it been used to develop a sustainable supplier selection process.

Although applications of SMCDM to address uncertainty are still limited, we should acknowledge the extensive literature on addressing uncertainty in the field of supplier selection (Chen et al., 2020; Ecer & Pamucar, 2020). While research continues to address uncertainty in supplier selection, the type of uncertainty that is often observable in the previous studies is different from what CST (or SMCDM) does. The previous studies commonly deal with fuzzy reasoning or linguistic expressions from decision makers (e.g. regarding the weightings or scores assigned to decision criteria or alternatives) rather than a set of future events. Although CST and fuzzy logic were both proposed by Zadeh (1968, 2016), they are completely different concepts. Fuzzy logic deals with partial truth (intervals rather than crisp sets) whereas CST deals with the stochastic natures of problems (Asadabadi & Zwikael, 2021). Subsequently, Asadabadi's proposal of SMCDM (2018) deals with different sets of criteria weightings, each of which is the result of the occurrence of an event (or multiple events). Although the original proposal of the SMCDM method was not able to consider more than a few events, this has later been resolved (Asadabadi & Zwikael, 2021).

We should also note that there is ongoing research on the application of scenario-based approaches in different fields (Hu & Dong, 2019; Oliveira et al., 2018). The related research in the field of supplier selection often considers various scenarios to handle uncertainty in demand and cost, based on which a supplier selection decision can be made [see Li and Zabinsky (2011), Kumar et al (2017), Balcik and Ak (2014), Olanrewaju et al. (2020), and Hemmati and Pasandideh (2021)]. In comparison with such studies, the current paper focuses on possible uncertainty in the weightings of the selection criteria under different scenarios. In a more telescopic view, this paper also contributes to advancing scenario-based approaches by showing how a very large number of scenarios (which can be based on the occurrence of several events) can be handled, and scenarios worth considering can be identified (see Sect. 4.4). This may help the generalisation of current scenario-based approaches.

In summary, supplier selection is a long-term decision, and in long-term decisions, the decision-makers' concerns also need to be considered regarding the future in which likely events may occur and impact the decision criteria weightings. This study utilises the SMCDM method (Asadabadi, 2018) which is fundamentally designed to deal with such uncertainty. The proposed framework also utilises BWM and TOPSIS to calculate the criteria weightings under the occurrence of each of the events and to compute the optimal supplier rankings. The next section explains how these methods can be combined to develop this supplier selection method.

3 Research methodology

IES-based supplier selection requires the consideration of multiple criteria. The IES criteria for this decision are extracted from the literature. The available suppliers need to be assessed with respect to the extracted criteria and subsequently, scores are assigned to them. Then, taking into consideration the weightings of the criteria, the outperforming supplier is selected.

This supplier selection process is usually a long-term decision. A challenge facing long-term decision-making is the computation of the weights of the selection criteria. Often, when decision-makers are required to assign weightings of importance to the criteria for a long-term decision, they become concerned about what the future may look like. This is because the future is uncertain and they may need to consider which likely events may occur in the

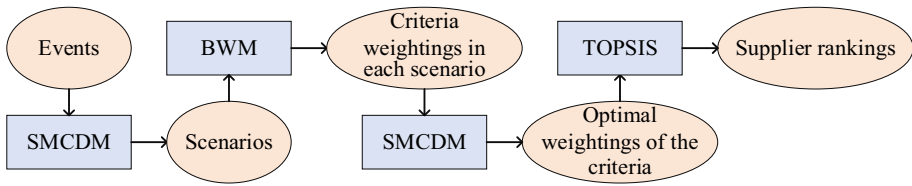


Fig. 1 The proposed decision framework utilising SMCDM, BWM, and TOPSIS

future and if so, how this may affect the criteria weightings. For example, in the decision-making process of buying a house, the selection criteria can be the size of the house, its accessibility, and its price. The following events may concern the person and impact the decision: *Event A*: a predictable recession in the market; *Event B*: a financial situation for the person; *Event C*: job promotion; *Event D*: enacting law to provide financial assistance to home buyers. These events result in several scenarios, where the occurrence of each will change the relative importance of the selection criteria. To say it differently, if the decision-maker assumes that *Event A* happens, they may assign a specific weighting for the criteria which is probably different than when they assume *Event B* happens. Such likely events and their combinations can be structured utilising the SMCDM method through the consideration of a range of possible scenarios as presented in Fig. 1. The consideration of scenarios enables the decision-maker to provide separate weightings of importance, based on which the optimal ranking of the available options is computed.

In this process, BWM is utilised to facilitate the process of obtaining the weightings of importance in each scenario from the decision-maker. After finding the optimal weightings of the decision criteria, TOPSIS is utilised and facilitates the process of computing the optimal ranking of the suppliers. In this way, a combined S-BWM-TOPSIS is developed. The steps of the methodology are as follows.

Step 1: Identifying events

In this step, experts are required to identify events that seem likely to occur in the future and impact the weightings of the selection criteria. To facilitate this process, the decision-maker may consider each of the selection criteria separately and identify those events (if any) whose occurrence has an impact on the importance of the criterion. Then, a collection of events is identified. The decision-maker needs to estimate the likelihood that the event happens and the likelihood that no events happen. The authors suggest the decision-maker utilises the most updated information to support their estimations. Such information can be accessible by contacting authorities in other organisations or referring to published information online or using accessible databases. Ultimately, the decision-maker is the one who decides on the values for estimations. Note that it is not necessarily a drawback to utilise the decision-maker's intuitive estimations. In many cases, such as applications of Bayesian networks (Varshney et al., 2017) or risk registers in projects (Merikhi et al., 2020), the best way to find the probability of future events is to directly obtain them from senior managers, authorities, and decision-makers. Even if we assume there is a level of inaccuracy in the decision-maker's estimated values, the consideration of different scenarios with a reasonable degree of inaccuracy in likelihood is much better than not considering such future events at all.

Step 2: Identifying possible scenarios

Based on the events that are identified, different scenarios need to be considered. One scenario represents the persistence of the current situation, or in other words, if nothing happens

(this scenario forms stratum one). For the occurrence of each event, one scenario is considered (these scenarios are in stratum two). These events can also occur together, so for each combination, one scenario is considered (these scenarios are in the next strata depending on the number of events that contribute to create the scenario). A challenge in this step can be the number of scenarios, which is exponentially increasing by increasing the number of events (for n events, 2^n scenarios need to be considered). Where the number of scenarios is more than what we wish to consider in the computation process, we need to determine a threshold and only consider scenarios that have likelihoods above the threshold. While the lower the threshold, the more accurate the results, we should also note that this means a higher volume of computations. The detailed process of considering several events and reducing the number of scenarios was explained by Asadabadi and Zwikael (2021), so it is excluded from the scope of this paper. Unlike their paper, in the current paper, only a few events are considered due to the paper's scope of proposing a novel solution to IES supplier selection.

Step 3: Computing transition probabilities

If the identified events are not independent, the likelihood of the occurrence of scenarios needs to be estimated by the decision maker. In cases where events are independent, or else have a negligible impact on each other, the probability of a scenario is calculated by multiplying the events that contribute to create that scenario. The process of computing transition probabilities is explained in detail in the case study.

Step 4: Computing the weightings of the criteria for each scenario separately

Scenarios and their likelihoods were determined in the previous steps. In this step, BWM is used to compute the weightings of importance of criteria. There are a few reasons why BWM has been selected for this step. In comparison with other popular MCDM techniques, such as the analytic hierarchy process (AHP), BWM requires fewer pairwise comparisons. As our proposed framework runs the selected method once for each scenario, BWM can dramatically reduce the amount of effort the decision maker needs to make. Moreover, as BWM requires fewer pairwise comparisons, it is also less likely to face the inconsistency issue, which may require the comparisons to be repeated. Furthermore, BWM starts by requiring the decision maker to identify the best and worst criteria. This helps the decision maker identify the differences between criteria weightings when considering different scenarios separately, and subsequently, it is less likely that dramatic mistakes will be made. Finally, BWM requires only two vectors, one for rating the best criterion to others and the other for rating the worst criterion to others. The rest is solved as an optimisation problem, and hence, there is less room for anchoring bias or human mistakes. The BWM procedure is set out in the following five sub-steps.

Sub-step 1: Attribute selection for analysis.

Sub-step 2: Of the selected attributes, the best and the worst ones are determined.

Sub-step 3: Each expert, using a scale of 1 to 9, provides their preference rating for the best attribute selected over all other attributes.

Sub-step 4: Each expert, using a scale of 1 to 9, provides their preference rating of all attributes over the worst attribute.

Sub-step 5: The optimised weightings (w_1^ , w_2^* , ..., w_n^*) of all attributes are calculated. The weightings of attributes need to be obtained where the maximum absolute difference for all j is minimised for $\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$. This means the following*

minimax equation will need to be solved:

$$\begin{aligned}
 & \min \max \{ |w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W| \} \\
 & \text{s.t} \\
 & \sum_j w_j = 1 \\
 & w_j \geq 0, \text{ for all } j
 \end{aligned} \tag{1}$$

Equation (1) can be transformed into a linear model in order to provide straightforward results:

$$\begin{aligned}
 & \text{Min } \xi^L \\
 & \text{s.t} \\
 & |w_B - a_{Bj}w_j| \leq \xi^L, \text{ for all } j \\
 & |w_j - a_{jW}w_W| \leq \xi^L, \text{ for all } j \\
 & \sum_j w_j = 1 \\
 & w_j \geq 0, \text{ for all } j
 \end{aligned} \tag{2}$$

By solving Eq. (2), values for optimal weightings ($w_1^*, w_2^*, \dots, w_n^*$) and optimal value ξ^L are computed.

Step 5: Calculating the optimal weightings of criteria

The weightings of criteria under different scenarios are computed in Step 4. These weightings build an $n \times m$ matrix (the first matrix in Eq. (3)) in which the columns represent the scenarios and the rows are the criteria. In this matrix, a_{ij} is the array on the i th row and j th column and represent the weighting of criterion i in scenario j . The second matrix in Eq. (3) includes the probabilities of scenario 1 to m . The multiplication of these two matrix results in a $n \times 1$ matrix that includes the optimal weightings of criteria.

$$\begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & & \vdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \times \begin{bmatrix} p_1 \\ \vdots \\ p_m \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix} \tag{3}$$

Step 6: Assigning scores to available suppliers and finding their ranking

The optimal weightings of the criteria obtained in Step 5 are used in this step to compute the supplier rankings. To facilitate this process, TOPSIS, which is a popular method in the literature, is selected (Silva et al., 2018). Similar to BWM which is a good choice to compute criteria weightings under different scenarios, TOPSIS is also a good choice for providing a suitable platform to find the optimal rankings of the suppliers. There are several reasons for selecting TOPSIS. To begin with, it is straightforward to use, yet it provides comparable results with more complex MCDM methods (Lahri et al., 2021). It also has the universality characteristic which makes it familiar to many researchers and practitioners (De Souza et al., 2018). Our proposed criteria decision framework already utilises three MCDM methods and it is good to avoid using a complex or confusing method at this stage. There are other reasons to support the choice to use TOPSIS. For instance, TOPSIS assesses the distances to an ideal solution. The preferred option is the one with the lowest geometric distance from the positive ideal solution (PIS) and the one with the most significant geometric distance from the negative ideal solution (NIS) (Hwang et al., 1993). Unlike other MCDM methods such as AHP or simple additive weightings (SAW), TOPSIS employs both maximising and minimising attributes directly. Such characteristics make the results robust and reliable (Lahri et al., 2021; Sharma et al., 2020; Yang et al., 2021). We should note that TOPSIS can be

criticised for issues such as rank reversal. However, such issues may also occur with even more severity when using other MCDM methods, such as AHP or EElimination and Choice Expressing REality (ELECTRE) (Liu & Ma, 2021).

As previously mentioned, TOPSIS is founded on the premise that the preferred option should be the one with the lowest geometric distance from PIS and the one with the most significant geometric distance from NIS. This compensatory aggregation approach enables a group of alternatives to be analysed by determining the weighting of each criterion, normalising scores for each criterion, and computing the geometric distance between each alternative and the ideal option, which has the highest score for each criterion (Huang et al., 2011).

Generally, in multi-criteria decision-making problems, normalisation becomes essential since parameters or criteria are often of discordant dimensions (Locatelli & Mancini, 2012). TOPSIS, and other compensatory approaches, allow for trade-offs between criteria, where a positive result in another might offset an adverse outcome in one criterion. This is particularly helpful in our case of supplier selection as it still allows the selection of suppliers, which are performing well with respect to some criteria even though they may fall behind in some criteria. For the purpose of normalisation, *vector normalisation* is used. There are other alternative approaches to use such as linear sum-based normalisation, linear max normalisation, linear max–min normalisation, among many others. We did not focus on comparing TOPSIS normalisation approaches, as it was not within the scope of this paper (only an application of a straightforward version of TOPSIS). However, several studies particularly focus on investigating different normalisation approaches. Some of them report no dramatic change in results using different normalisation approaches, others suggest the selection of vector normalisation when considering elements such as the consistency level (Çelen, 2014; Lu et al., 2011; Vafaei et al., 2018; Zaidan & Zaidan, 2018). We should note that these studies make some assumptions and also do not comprehensively consider all normalisation approaches. We should also note that there are several versions of TOPSIS which utilise innovative normalisation approaches. Such innovative proposals can also be considered to enhance this paper's proposal (see e.g., do Carmo Silva et al. 2020). The steps of TOPSIS are presented below.

Sub-step 1: Calculate the normalised $k \times j$ decision matrix, where the k represents the k th alternative j represents the j th criterion. The normalised value of \overline{X}_{kj} is computed as presented in Eq. (4):

$$\overline{X}_{kj} = X_{kj} / \sqrt{\sum_{k=1}^p X_{kj}^2} \quad (4)$$

Sub-step 2: Calculate the normalised decision matrix as follows:

$$\overline{X}_{kj} = X_{kj} / \sqrt{\sum_{k=1}^p X_{kj}^2} \quad (5)$$

where w_j is the weighting of the j th attribute/criterion and $\sum_{j=1}^n w_j = 1$.

Sub-step 3: Determine the following two solutions: the positive ideal (A^+) and the negative ideal (A^-).

$$A^+ = \{v_1^+, \dots, v_n^+\}, \text{ where } v_j^+ = \{\max(v_{kj}) \text{ if } j \in J; \min(v_{kj}) \text{ if } j \in J'\}, j = 1 \dots n \quad (6)$$

$$A^- = \{v_1^-, \dots, v_n^-\}, \text{ where } v_j^- = \{\min(v_{kj}) \text{ if } j \in J; \max(v_{kj}) \text{ if } j \in J'\}, j = 1 \dots n \tag{7}$$

Sub-step 4: Calculate the separation measures utilising the m -dimensional Euclidean distance. The separation measures of alternatives are as follows where Eq. (8) represents the positive ideal solution and Eq. (9) is the negative ideal solution):

$$S_k^+ = \left\{ \sum_{j=1}^n (v_{kj} - v_{kj}^+)^2 \right\}^{1/2}, k = 1 \dots p \tag{8}$$

$$S_k^- = \left\{ \sum_{j=1}^n (v_{kj} - v_{kj}^-)^2 \right\}^{1/2}, k = 1 \dots p \tag{9}$$

Sub-step 5: Calculate the relative closeness to the ideal solution, the relative closeness of the alternative A^+ with respect to A^- :

$$R_k = \frac{S_k^-}{S_k^- + S_k^+} k = 1 \dots p \tag{10}$$

Sub-step 6: Rank the alternatives.

The supplier with the highest ranking is the best supplier and is introduced to the organisation. In the next section, a case study illustrates how this methodology is implemented in practice.

4 Practical application and analysis

4.1 Case problem description

The case study of this paper is conducted in Iran, which is a developing country in the Middle East. The identity of the case study company is not revealed in this section and is referred to as Company *xyz*. This, however, does not impact the aim of this section which is to show how the proposed framework works. Company *xyz*, located in the central part of Iran, is a leading automotive manufacturer. It was established a few decades ago and since then, has manufactured and assembled a variety of vehicle types, and is exporting products to a few Asian countries. This corporation follows IES fundamentals in many decisions they make and was interested to participate in this research. A committee of five senior managers, namely a purchasing manager, a logistic manager, a supply manager, a financial manager, and a general manager, was formed. Each of the decision-makers had at least 10 years of working experience. These decision-makers are extremely expert and knowledgeable in their specific field. According to Rezaei et al. (2012) in expert-based methodologies we can rely on a small sample of experts. There are several papers in the published literature that have used small number of experts in the assessment process (e.g. Ahmadi et al., 2021; Vafadarnikjoo et al., 2021).

4.2 Constructing the evaluation framework of the study

This sub-section explains the development process of the evaluation framework of the study. A survey using the criteria in Table 1 was developed and emailed to these managers. The

survey also required information to identify the criteria which were more applicable to their supply chain operations by indicating either (Yes) as accepted, or (No) as rejected (they were also given the opportunity to suggest other related environmental innovation criteria). The managers agreed that criteria which were approved by at least three managers would be considered in the next round of review. In total, three rounds of reviews were carried out in the criteria refinement process. Ultimately, the following five criteria were selected. C1: Application of policies related to the environment as well as demands in the market; C2: Investing in the environment to make an economic gain; C3: Resource accessibility as well as green competencies; C4: Collaborating with rivals and groups related to the environment; and C5: Product design considering factors such as reusing and being energy efficient.

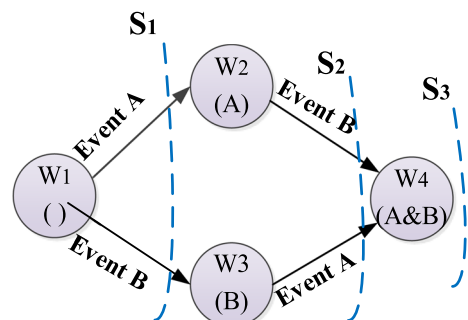
Moreover, the managers shortlisted five of their top suppliers to participate in this research. These five suppliers are evaluated based on their environmental sustainability innovation implementation levels. Several papers in the published literature have employed this screening approach and used decision-makers input for the qualification purpose, i.e. whether a particular factor should be included or not for the assessment phase (see for example Ahmadi et al., 2017; Ahmadi et al., 2021).

4.3 Application of the S-BWM-TOPSIS to the case

The methodology presented in Sect. 3 is utilised here to find the best supplier for this case study to support their IES strategy.

Step 1 of the method identifies the likely events whose occurrence may change the weightings of the IES criteria. These events can be extracted in the meetings of senior decision makers with the aforementioned committee members. Assume the decision maker is concerned that the following events may impact the weightings they assign to the selection criteria. Event *A*: possible long-term market recession (following the COVID-19 pandemic); and Event *B*: reduction of government financial support (for this industry). Assume event *A* and *B* currently have the likelihoods 50% and 25% respectively. The estimation for the persistence of the current situation (the occurrence of no event) is 37.5%. Step 2 identifies the resulting scenarios. In cases where several events are involved, the stratified tables can be utilised to facilitate the process of identifying which scenarios should be considered in each stratum before reaching that stratum (Asadabadi & Zwikael, 2021). But, as there are only a small number of events, the stratified figure is sufficient to visualise this process. Possible scenarios for this case study are presented in Fig. 2 (where S_n stands for n th stratum). Event *A* and *B* result in four different scenarios labelled W_1 to W_4 .

Fig. 2 The graph of events and the resulting possible scenarios



Step 3 computes how probable it is that each of the four scenarios will occur in the future. As previously mentioned, the estimates of the likelihood of the occurrence of no events, event *A* and event *B* are 37.5%, 50% and 25%, respectively. These values indicate that the probability of the occurrence of event *A* (scenario W_2) is twice that of event *B* (scenario W_3) and 1.33 times the occurrence of no events (scenario W_1). The simultaneous occurrence of event *A* and *B* creates scenario W_4 . If the events that create a scenario are not independent, the decision-maker needs to provide an estimation for its likelihood as well. However, it becomes more interesting when events are independent as, in this case, the probability of each scenario which requires more than one event to create it, will be equal to the multiplication of the probability of events that create the state. For example, in this case, as W_2 and W_3 are 1.333 and 0.667 times the probability of Scenario W_1 , the probability of W_4 will become 0.889 times (1.333×0.667) the square probability of W_1 . As these scenarios are all possible given the two events (event *A* and *B*), the sum of the probabilities of these four scenarios must be one. This results in solving the following equation (in which P_1 denotes the probability that the future turns out to be scenario W_1).

$$0.89P_1^2 + 3P_1 = 1 \tag{11}$$

The valid answer for this equation is 0.305. Given this, the transition probability matrix, or P_t , is as follows:

$$P_t = \begin{matrix} P_1 \\ P_2 \\ P_3 \\ P_4 \end{matrix} \begin{bmatrix} 0.305 \\ 0.408 \\ 0.204 \\ 0.083 \end{bmatrix} \tag{12}$$

As presented in the methodology, Step 4 comprises several sub-steps to employ BWM and calculate the criteria weightings. The weightings of the selection criteria need to be computed separately for scenario W_1 to W_4 . Therefore, the BWM steps (*Sub-step 1* to *Sub-step 5*) have been followed. The resulting weightings are presented in matrix M_{CW} .

$$M_{CW} = \begin{matrix} W_1 & W_2 & W_3 & W_4 \\ \begin{matrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \end{matrix} & \begin{bmatrix} 0.222 & 0.233 & 0.196 & 0.200 \\ 0.261 & 0.192 & 0.349 & 0.239 \\ 0.117 & 0.158 & 0.242 & 0.202 \\ 0.175 & 0.301 & 0.100 & 0.255 \\ 0.225 & 0.116 & 0.113 & 0.105 \end{bmatrix} \end{matrix} \tag{13}$$

As explained in Step 5 of the methodology, matrix M_{CW} is multiplied by the transition probability matrix (matrix P_t). This results in a single column matrix, which includes the optimal weightings of the criteria as presented in matrix M_C .

$$M_C = \begin{matrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \end{matrix} \begin{bmatrix} 0.219 \\ 0.249 \\ 0.166 \\ 0.218 \\ 0.148 \end{bmatrix} \tag{14}$$

Table 2 Normalised scores assigned to suppliers

	C_1	C_2	C_3	C_4	C_5
Supplier A	0.346	0.421	0.564	0.372	0.476
Supplier B	0.346	0.395	0.596	0.521	0.452
Supplier C	0.598	0.342	0.361	0.447	0.500
Supplier D	0.551	0.447	0.314	0.410	0.393
Supplier E	0.315	0.592	0.314	0.472	0.405

Table 3 S-BWM-TOPSIS final rankings

Suppliers	S_{k+}	S_{k-}	R_k	Rank
Supplier A	0.077	0.048	0.385	5
Supplier B	0.074	0.060	0.445	4
Supplier C	0.075	0.067	0.470	1
Supplier D	0.067	0.059	0.468	2
Supplier E	0.080	0.066	0.452	3

In Step 6, the five decision makers involved in this study are asked to assign scores to potential suppliers. The data coming from different decision makers (Appendix 1) can be taken into consideration differently through computing a weighted average of the data they provide. The weighting assigned to each decision maker can be based on factors such as their related experience, their levels of confidence, and similar. However, in this case study, the company advised us to avoid ranking their managers and consider them as different viewpoints which are equally important. So, the simple average scores are used as the inputs to the TOPSIS to identify the optimal rankings. Table 2 displays the normalised scores for suppliers with respect to the criteria.

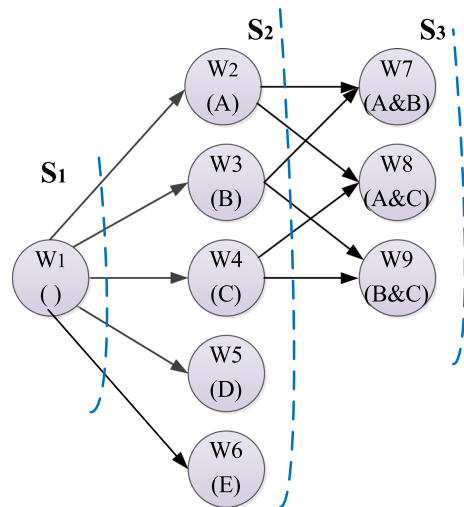
The weightings of the criteria (values in matrix M_C) are then multiplied by the respective column in Table 2. This is followed by applying sub-steps 3 to 5 in the 6th step of the methodology, and the results are presented in Table 3.

The optimal rankings of these potential suppliers are presented in the last column of Table 3. The rank column shows that considering the IES criteria and potential future events, supplier C is the best supplier for this company. In other words, supplier C will perform the best in terms of achieving the IES goals of the company. However, we should note that this may not represent the final ranking of the suppliers, as this is just regarding IES criteria. Suppliers need also to be ranked regarding other criteria, such as economic, social, quality, cost, and similar. These criteria may then be weighted, the final scores of the suppliers may be computed, and these final scores will represent the ultimate ranking of the suppliers.

4.4 Extending the dimensions of the case study

The case discussed in this section only included two events. However, there might be cases where more events need to be considered. Where the number of events increase, the number

Fig. 3 The graph for five events and the resulting possible scenarios



of scenarios exponentially increase. This can be a challenge hindering the future applications of the proposed decision framework. For instance, for five events, there will be more than 32 scenarios to consider. While this was not the case in the above example, to guide the future applications of the proposed framework, we assume that there is a case with five likely events and show how the number of scenarios can be reduced to a manageable number. Assume that the likelihoods of no event occurring, event A, B, C, D, and E, are 30%, 40%, 25%, 20%, 10%, and 10% respectively. Here, we already have six scenarios as represented in Fig. 3. The first one is where nothing happens. The following five scenarios represent the occurrence of each of these five events. There will be 26 other scenarios to consider. However, not all these scenarios are worth considering, the reason being that some of these scenarios will have low likelihoods, and subsequently, the computed probabilities for them will be even lower and ignorable. This means that even if we consider all these less likely scenarios and compute the weightings of the criteria in these scenarios, their impact on the optimal weightings will be ignorable due to the low probability of the scenarios. Therefore, a threshold can be considered and scenarios that have likelihoods below the threshold are eliminated from further consideration. This threshold needs to be determined by the decision maker keeping in mind that the higher the threshold, the lower the number of scenarios to consider and the less amount of computation. However, selecting a large number as the threshold can also impact the accuracy. So, it will be the matter of striking a balance between the desired level of accuracy and the subsequent amount of calculation.

Let's assume that the decision maker selects 5% as the threshold in this example. Assuming that these events are independent, the likelihoods of scenarios that are the results of the occurrence of multiple events can be estimated by multiplying the likelihoods of those multiple events. Therefore, in our example, only the combination of event A, B, and C, need to be added as the additional states as presented in Fig. 3. This is because multiplying other likelihoods will result in a number less than 5%. As previously mentioned, selecting a lower number, e.g. 2%, will result in the consideration of more scenarios.

After determining the likely scenarios, BWB is used to compute the weightings of criteria in each scenario, and SMCDBM computes the weightings (which can be claimed to be almost the optimal weightings). One may argue what if some of the events are not independent. For

such cases, likely scenarios (to be considered) need to be determined by the decision maker, which can be studied further in the future.

5 Comparative analysis

This study combines SMCDM, BWM, and TOPSIS to provide an integrated tool to address the IES supplier selection problem. The literature has already provided integrations of BWM and TOPSIS (Gupta, 2018; Lahri et al., 2021). Hence, the methodological novelty of this paper is in terms of integrating SMCDM with BWM-TOPSIS (see Fig. 1). Given this, the performance of the proposed framework is compared against the BWM-TOPSIS method. Using BWM-TOPSIS (without the consideration of the scenarios) means computing the criteria weightings (under the current scenario) using BWM and then finding the optimal weightings of the suppliers using TOPSIS. The optimal weightings of criteria under the current scenario using BWM are presented in Matrix 15.

$$M_{C2} = \begin{matrix} C1 \\ C2 \\ C3 \\ C4 \\ C5 \end{matrix} \begin{bmatrix} 0.222 \\ 0.261 \\ 0.117 \\ 0.175 \\ 0.225 \end{bmatrix} \tag{15}$$

Using these values as the weightings of the criteria, the final results of the BWM-TOPSIS method are presented in Table 4.

We can see that not only the values, but also the rankings of the suppliers in Table 4 (BWM-TOPSIS) are different from those in Table 3 (S-BWM-TOPSIS). Using BWM-TOPSIS, supplier *D* is the highest-ranked supplier while using S-BWM-TOPSIS, Supplier *C* takes the first place (Table 3). This shows that the results using S-BWM-TOPSIS may dramatically be different from BWM-TOPSIS. The cause of this difference is as follows. In BWM-TOPSIS, we can only consider one set of weightings for our IES decision framework. This is usually based on the current weightings, decision makers assign to IES criteria (Matrix (15), which is also the same as the first column in Matrix (13)). It can also be based on their estimate of the future weightings (which can be intuitively). One way or the other, only one set of weightings is assigned to IES criteria. However, in the stratified based model, we have different sets of criteria weightings (presented in four columns of Matrix (13)). This includes the current

Table 4 BWM-TOPSIS results

Suppliers	S_{k+}	S_{k-}	R_k	Rank
Supplier <i>A</i>	0.076	0.041	0.350	5
Supplier <i>B</i>	0.077	0.047	0.379	4
Supplier <i>C</i>	0.072	0.069	0.489	2
Supplier <i>D</i>	0.060	0.060	0.498	1
Supplier <i>E</i>	0.075	0.068	0.475	3

weightings of criteria (first column of Matrix (13)), and the future weightings of criteria under different scenarios (second, third, and fourth column of Matrix (13)). These weightings are combined with respect to the probabilities of persisting the current situation (first row in Matrix (12)) or transitioning to any of these event-based scenarios (second, third and fourth rows in Matrix (12)). Then, the optimal set of criteria weightings is computed (Matrix (14)). If values for these optimal weightings in S-BWM-TOPSIS (presented in Matrix (14)) are close to the criteria weightings in BWM-TOPSIS (presented in Matrix (15)), it becomes more likely that we observe minor changes in results of BWM-TOPSIS and S-BWM-TOPSIS. However, in the above case, the difference in values of Matrix (14) and (15) was sufficient to change the ranking of the suppliers.

However, the question now may be raised as to which ranking is more reliable for organisations to use. As discussed earlier in the paper, S-BWM-TOPSIS is equipped with the stratified approach (Asadabadi, 2018; Asadabadi & Zwikael, 2021), which is basically designed to consider different scenarios. This means that this approach does not make the decision solely based on the current (or most likely) scenario. This further means that the decision maker's concerns about what the future would be are taken into consideration in Table 3's ranking while this cannot be considered using BWM-TOPSIS (Table 4). Therefore, we claim the resulting values and supplier rankings presented in Table 3 are more reliable than those in Table 4 as they take into computation the decision maker's uncertainty about the future before suggesting which supplier is the best with which to proceed. Moreover, S-BWM-TOPSIS considers a range of scenarios in the process of computing supplier rankings—whereas BWM-TOPSIS cannot consider more than a single scenario. Given this, if a decision maker makes a mistake regarding the weighting of a criterion in BWM-TOPSIS, the supplier rankings may considerably be impacted. By contrast, in S-BWM-TOPSIS, if the decision maker makes a mistake regarding the weightings of a criterion, because there will be multiple sets of criteria, this mistake will be moderated in the process of combining these weightings and may influence the results in a smaller scale.

6 Discussion

Innovation for sustainability is becoming an integral part of the long-term strategies of organisations (Cui et al., 2021; Tsolakis et al., 2021). With the emphasis which governments and society put on the environmental aspects of innovation for sustainability, the growth of IES as a distinct field in the literature is not a surprise (Ecer & Pamucar, 2020). Despite the progress researchers have made in this field, the main research directions still focus on explaining the factors that impact the implementation of IES strategies in organisations, or the organisational endeavours that can be affected by IES implementation (Bui et al., 2020). Different from the existing literature in this field, this research paper is the first to propose an IES-based supplier selection framework. To do so, the paper investigates the literature, identifies key criteria, and develops an innovative decision framework to find the supplier that supports the best IES implementation in organisations.

Supplier selection is a key decision in organisations and the best supplier may differ depending on what long-term strategies an organisation implements (Nair et al., 2015). Research has employed a variety of MCDM techniques to tackle this problem (Hadian et al., 2020). The available suppliers are assigned scores with respect to the selection criteria, and then based on the weightings of the selection criteria, their rankings are computed. However, these rankings may not be an effective indication of the best supplier to support a long-term

decision. The selected supplier often needs to remain in service for a relatively long period of time to provide goods or services to the organisation. To develop an effective decision-making framework, the decision criteria need to have weightings that take into consideration the uncertainty of the future in which the supplier will be operating. Where the uncertainty level is high, such as after the recent outbreak of COVID-19, it becomes even more important to integrate uncertainty into the decision-making processes. To date, there is limited research to show how to develop a decision framework to integrate such uncertainty and assist decision-makers in practice. This research gap hinders the proposal of an IES supplier selection framework. This is because utilising a decision framework that does not consider such uncertainty may result in choosing a supplier which may be the best IES supplier in the current situation but may very likely be outperformed by other potential suppliers in the future. If so, the organisation may need to select a new supplier which hinders the development of a long-term relationship in a supply chain. To address this issue, this paper suggested the application of three MCDM methods to develop an IES supplier selection framework. The first is the recently developed MCDM method, namely the SMCDM method, which can incorporate uncertainty into decision-making processes. Despite the innovative insights the SMCDM method brings to the MCDM literature, the original proposal (Asadabadi, 2018) does not provide an approach to obtain the weightings of the decision criteria in different scenarios. This paper employs BWM to improve the SMCDM method and increase the accuracy of the process of decision-making and TOPSIS to facilitate the process of ranking suppliers based on the identified IES criteria.

The decision framework discussed in this paper, labelled S-BWM-TOPSIS, has a few important managerial implications. This paper provides managers and decision makers in organisations with a set of IES criteria that can be utilised to support their supplier selection decisions. Moreover, this work develops an innovative criteria decision framework which can be used in practice to select the right supplier. The proposed framework can also be employed by organisations to address problems managers may face in the broader domain of operations management—when a long-term decision is to be made under uncertainty (e.g. launching a new production line in the current uncertain world of COVID-19). As mentioned in the previous section, the proposed S-BWM-TOPSIS framework has merits over BWM-TOPSIS, including its ability to consider uncertainty related to concerns managers and decision makers may have regarding the occurrence of future events. This characteristic is a result of equipping BWM-TOPSIS with the SMCDM method which was originally proposed in the literature to deal with such concerns (Asadabadi, 2018). Therefore, even if practitioners use other decision-making methods in their organisations, and they still want to empower their existing methods to take into account such managerial concerns, this paper can provide guidance. As set out in the methodology section, BWM and TOPSIS are presented in different stages with explicit steps and can easily be replaced with other MCDM methods (and similar frameworks to our proposal can be developed). Regarding the current proposal of S-BWM-TOPSIS, a general recommendation to any organisation wanting to utilise this method is that it is best if this combined method is used as is. However,

- if the organisation does not see the future as highly uncertain, they may opt to exclude the SMCDM method from the framework (BWM-TOPSIS).
- if the organisation does see the future as uncertain but they are confident about the weightings that they have assigned to the selection criteria, they may remove the BWM method (S-TOPSIS).

- if the organisation is not sure about the future and also the weightings of the selection criteria but they are relatively confident about the scores suppliers receive with respect to the criteria, they may remove TOPSIS method (S-BWM).

In addition, the consideration of a range of positive and negative events (and subsequently scenarios) makes managers and decision-makers more realistic in the decision-making process. This is because such consideration, somehow, quantifies uncertainty and this reduces the room for bias or being too optimistic or pessimistic. Furthermore, the SMCDM method enhances communications about events and their impacts in organisations in the hierarchy. This collaborative evaluation and analysis process to compute the optimal weightings of the IES criteria may help them become familiar with each other's ways of thinking and this may also reduce potential conflicts. Finally, this process can reveal to executives and decision makers some likely events (and their consequences) that they were not aware of. This may enhance the quality of the other decisions they make in the organisation.

7 Conclusion

The consideration of sustainability innovation criteria in supplier assessment assists corporations to attain their sustainability targets. This paper utilises the existing literature to extract the most important IES criteria, which can potentially be employed to develop an effective decision framework for supplier selection. This article is the first to introduce a criteria decision framework consisting of a list of environmental innovation criteria to assess potential suppliers in order to support the organisation's environmental innovation performance. Moreover, a novel methodology (labelled S-BWM-TOPSIS) was also developed. This proposal enables authorities and decision-makers in emerging economies—with a high level of uncertainty—to take into their decision processes the uncertainty related to the occurrence of a range of events in the future.

Despite the merits of the proposed S-BWM-TOPSIS framework, it has limitations. One limitation is the subjectivity of the transition probabilities used in this method. These estimations are obtained from decision-makers and in some cases, they can be quite subjective. This may become problematic in future applications of the STOPSIS method. However, we should note that even assuming that there is a level of inaccuracy in the estimations provided by the decision-maker, considering different scenarios and integrating them into the decision-making process is much better than not considering them at all. The same subjectivity concern can also be applied to obtaining the decision criteria weightings in different scenarios. Such subjectivity may be addressed in future studies using soft computing techniques such as fuzzy logic. Another limitation is that the decision framework, developed in this paper, consists of only five broad criteria for environmental sustainability innovation. We suggest future studies include several sub-criteria related to each criterion which can lead to more customised and comprehensive analysis.

Appendix 1: Scores assigned to the potential suppliers

See Tables 5, 6, 7, 8 and 9.

Table 5 Scores assigned to suppliers by expert 1

	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>
Supplier <i>A</i>	2	3	3	2	5
Supplier <i>B</i>	1	5	4	2	3
Supplier <i>C</i>	2	2	3	4	5
Supplier <i>D</i>	3	4	2	5	4
Supplier <i>E</i>	3	3	2	3	1

Table 6 Scores assigned to suppliers by expert 2

	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>
Supplier <i>A</i>	1	3	3	4	2
Supplier <i>B</i>	2	4	5	5	3
Supplier <i>C</i>	2	1	1	4	4
Supplier <i>D</i>	2	3	3	4	5
Supplier <i>E</i>	1	2	3	3	4

Table 7 Scores assigned to suppliers by expert 3

	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>
Supplier <i>A</i>	2	4	4	3	2
Supplier <i>B</i>	3	3	4	5	5
Supplier <i>C</i>	4	5	4	3	1
Supplier <i>D</i>	3	2	2	1	1
Supplier <i>E</i>	2	4	3	4	5

Table 8 Scores assigned to suppliers by expert 4

	<i>C1</i>	<i>C2</i>	<i>C3</i>	<i>C4</i>	<i>C5</i>
Supplier <i>A</i>	4	3	5	2	3
Supplier <i>B</i>	3	3	5	5	4
Supplier <i>C</i>	1	2	2	4	3
Supplier <i>D</i>	4	3	2	4	3
Supplier <i>E</i>	2	4	5	5	2

Table 9 Scores assigned to suppliers by expert 5

	C1	C2	C3	C4	C5
Supplier A	2	3	3	2	1
Supplier B	2	4	5	4	4
Supplier C	1	3	2	3	4
Supplier D	3	5	4	4	5
Supplier E	2	3	3	4	5

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