Outsourcing modelling using a novel interval-valued fuzzy quantitative strategic planning matrix (QSPM) and multiple criteria decision-making (MCDMs)

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Abstract

Outsourcing drives companies to focus on: their capabilities, advantages of external resources, and decreasing overall operational costs. Selecting appropriate alliances, which are aligned with the company's strategies, establishes a situation through which the firms can enhance their technical capabilities and achieve new technologies. However, two critical issues in outsourcing modeling should be addressed: how to find strategic indicators for building successful alliances, and how to select these partners. Besides, as the imprecise and vague information (due to a lack of data) existing in the outsourcing models cannot be neglected, the application of fuzzy interval sets could efficiently address the complexity of these problems.

To deal with these issues, this paper proposes a two-step interval-based framework for the problem. At the beginning, and for the first time, the novel integration of an interval valued fuzzy (IVF) version of strength-weakness-opportunity-threats (SWOT) technique and the quantitative strategic planning matrix (QSPM) with Gap analysis is designed to find the most effective strategies for the alliance evaluation, and to weight them. In the next step, four interval-valued version of multiple criteria decision-making methods (IVF-MCDMs) are implemented to evaluate the strategic partners.

Finally, the results are aggregated with the help of the utility interval approach, and a sensitivity analysis is implemented to assess the robustness of the proposed methodology. To illustrate the efficiency of the proposed approach, a real partner selection problem at a holding car manufacturing factory in Iran is presented.

Keywords: Partner selection; MCDM; Outsourcing; Fuzzy interval modeling; strategic alliances.

1. Introduction

The most commonly defined concept for outsourcing is the transfer of activities and processes previously conducted internally, to an external (Ellram and Billington, 2001). Actually, outsourcing even domestically or internationally, has dramatically changed the competing frame of diverse industries like automobiles, aerospace, telecommunications, computers, pharmaceuticals, chemicals, healthcare, financial services, energy systems and software (Alikhani et al., 2019; Ciasullo et al., 2017). Undoubtedly, outsourcing drives companies to focus on their core organizational capabilities which in turn, frees critical resources for more profitable business units (Hätönen and Eriksson, 2009). Besides, the simultaneous applying and leveraging of external resources which results in a total decrease of operational costs and overall cost controlling, cannot be neglected. Outsourcing establishes a situation through which firms can enhance their technical capabilities such as achievement of new technologies, highly-skilled human resource; and compensate for any shortage of the latter (Ji et al., 2018).

However, the framework of outsourcing is significantly concerned with where to outsource, and in particular which partners/suppliers to select (Akhavan et al., 2015; Dey et al., 2015; Xie et al., 2016). Moreover, researchers have been interested in how to outsource or how to manage strategic decisions within the outsourcing process (Franceschini et al., 2003; Gunasekaran et al., 2015; Momme, 2002).

A growing trend is companies trying partnerships with other firms by providing strategic alliances with other suppliers in order to become involved in the competitive advantages of outsourcing (Inkpen and Ross, 2001). Therefore, the approach in this paper tries to explain how to select appropriate strategies in finding, then choosing proper partners/alliances. Wetzstein et al. (2016) proposed six main streams by a systematic assessment of supplier/partner selection (SS) literature including (1) solving approaches, (2) criteria for SS, (3) green and sustainable SS, (4) strategy oriented SS, (5) research and development (R&D) oriented SS, and (6) operation oriented SS. The current research includes the most frequent streams including the multiple solving approaches, criteria for SS, and strategy oriented SS.

1.1. Application of IVF-MCDMs for strategic alliances as the solving approach

The partner selection with multiple conflicting quantitative and qualitative criteria has been addressed as a multiple criteria decision-making (MCDM) problem (Wu and Barnes, 2011). On the other hand, due to the uncertainty and complexity of outsourcing data in reality, it is not usually possible to specify the importance of affecting criteria of outsourcing in an exact environment. Although it has been less considered in the appropriate literature, in this case, the application of interval-valued fuzzy (IVF) datasets to describe and treat imprecise and uncertain factors of the outsourcing problem could serve the purpose better (Pamucar et al., 2018; Ye, 2010). Therefore, the proposed research methodology approaches to the application of fuzzy interval sets, deals with the discussed outsourcing problem. However, application of fuzzy set theory to adapt to the uncertain nature of outsourcing problems has been examined by researchers and is known as a common technique in the literature (Chai et al., 2013; Keshavarz Ghorabaee et al., 2017). Keshavarz Ghorabaee et al. (2017) presented a comprehensive review of MCDM applications in the significant context of applying fuzzy set theory for supplier evaluation and selection problem. They categorized 339 related articles into two classes i.e., single approaches and hybrid approaches. They also found the most frequent approaches to be the analytic hierarchical process (AHP) and technique for order of preference by similarity to ideal solution (TOSIS), in both categories.

Specifically, IVF sets in comparison with triangular fuzzy sets, could share advantages in tackling the complexity of outsourcing models which have originated from vagueness (lack of sharp class of boundaries, especially in human judgment and preference) and lack of data (Gupta et al., 2018). Besides, similar applications of IVF sets via type-2 fuzzy sets introduces another considerable advantage to solving the problem (Büyüközkan and Göçer, 2018; Cornelis et al., 2006).

Consistent with this, the novel IVF quantitative strategic planning matrix (QSPM) with Gap analysis and IVF-MCDM which includes IVF-TOPSIS, IVF-ARAS (additive ratio assessment), IVF-SAW (simple additive weighting) and IVF-COPRAS (complex proportional assessment), are developed to tackle the problem of partner selection for strategic alliances.

1.2. Application of IVF-SWOT-QSPM as the criteria determination and strategy evaluation

Consequently, as for any MCDM problem, the determination of affective outsourcing criteria plays an essential role in the accuracy and validity of results, however this is rarely discussed in the literature of partner selection. In this research, the criteria affecting the strategic alliance partner selection are determined through a strategic planning process, i.e., the strength-weakness-opportunity-treats (SWOT) analysis, which is used to define the key criteria or strategies on the basis of effective internal and external factors of an outsourcing problem. From now on, the terms 'key criteria' and 'strategies' reflect the same concept and are used instead.

SWOT analysis is a strategic management tool used to identify the key internal and external factors that are important for the achievement of firms' goals (Hill and Westbrook, 1997). The major procedure followed by this method is summarized in two phases: firstly, determining criteria in the form of strengths (S), weaknesses (W), opportunities (O) and threats (T); the second phase then identifies the SO, WO, ST and WT strategies by a pairwise comparison of related criteria. In spite of potential benefits of the SWOT analysis in the partner selection process to define the affecting strategic criteria, there are two main problems with this method (Akhavan et al., 2015). The first one is associated with its inability to prioritize strategies, and the second is the large number of strategies generated by this method.

Therefore, weighting of criteria on the accuracy and validity of results is critical. Generally, in any MCDM problem, the criteria weight could be calculated based on three categories: subjective methods, objective methods and integrated methods (Dong et al., 2018). The subjective methods are used for calculating weights regarding the preference or judgments of decision-makers; whilst objective methods are used for determining attributes' weights through objective decision matrix information and mathematical models, such as entropy, analytical network processing (ANP) and data envelopment analysis (DEA), etc. The integrated method selects the criteria weight based on both judgments of decision-makers and objective decision matrix information (Barak and Dahooei, 2018).

To the best of the author's knowledge, few studies have addressed criteria weighting in partner selection, which is essential in this research. In support of this idea, the QSPM with Gap analysis is developed for the first time as an integrated technique to find the criteria weights. The output of this step relates to highlighting the most significant criteria that play the most important roles in the selection of a strategic alliance for partner selection. The achieved results are then inserted as the input data for applying MCDMs as a scientific way to decide on the candidate partners, and then rank them.

The contribution of the current research to the strategic alliance for partner selection problem, could be noted as: 1. The design of a novel strategy detection and weighting framework for the partner selection problem; 2. The development of an integrated feature weighting model with interval-valued SWOT-QSPM and Gap analysis as a novel technique to identify the most significant criteria; 3. The application of IVF-MCDMs to rank the partners according to uncertainty and vagueness of the outsourcing problem; 4. The integration of the obtained ranking with the utility interval approach.

The structure of this paper is as follows: section 2 articulates the existing methods of partner selection and strategic alliance – SWOT and QSPM. Section 3 explains the methodology that has been implemented for modeling and investigating the strategic alliance for partner selection. Section 4 describes the case-study and experimental results of the research. Section 5 presents the utility aggregation method to provide the final evaluation of the partners and to assist managers in selecting the best ones. In this section, the sensitivity analysis through the evaluation of possible deviation of weight values related to criteria has been undertaken to find out how robust the achieved ranking results and MCDM methods are. Moreover, a discussion on both the theoretical and practical implications of this research is presented. Finally, section 6 elucidates the contributions and indicates further scope of the research.

2. Literature review

Nowadays, selecting the most appropriate partners for manufacturing systems is regarded as a time-consuming and resource-intensive issue in everyday operations that can affect a company's operational success (Büyüközkan and Güleryüz, 2016). Hence, many studies have discussed the various aspects of this topic. In this paper, we generally identify the literature associated with the keywords: 'supplier selection', 'partner selection' and 'strategic alliance partner selection' and mostly application of MCDM as one of the most popular solving approaches to the problem. Weber et al. (1991) reviewed the criteria affecting the supplier/vendor selection problem. De Boer et al. (2001), looked at the proposed methods of supplier selection and offered a four-stage framework for the problem, comprising of formulation of criteria (finding out exactly what is to be achieved by selecting a supplier), qualification (qualifying suitable suppliers), final selection and application feedback. They concentrated on the advantage of applying operational research methods especially for the earlier stages of supplier selection processes.

Ho et al. (2010) proposed two main individual and integrated approaches to review the research from 2000 to 2008 for the supplier selection and evaluation problem. They concluded that the most popular implemented individual approaches were DEA (for its robustness), mathematical programming (MP), and AHP; and for the integrated approaches, combined models with AHP. Besides, quality, delivery, price/cost, manufacturing capabilities/services and management were implied as the most frequently applied criteria for the evaluation of suppliers. Wu and Barnes (2011) presented a literature review of decision-making models and approaches of partner selection, significantly those that are relevant to agile supply chains and in accordance with the four-stage framework presented by De Boer et al. (2001). They categorized articles of the partner selection problem published between 2001 and 2011, and concluded that most of them considered mathematical programming, AHP/ANP or a fuzzy set approach. Agarwal et al. (2011) presented another review of solving approaches for the supplier selection and evaluation problem. In their investigation, they tackled 68 scientific papers and found nine criteria to identify the classifications of the solving approaches: DEA, MP, AHP, ANP, fuzzy set theory, case based reasoning (CBR), simple multi attribute rating technique (SMART), genetic algorithm (GA), and criteria based decision-making, which were determined as the main criteria of their review.

Later, Chai et al. (2013) classified 123 published articles from 2008 to 2012 and provided a systematic review of the field, based on four perspectives: (1) decision problems, (2) decision-makers, (3) decision environments, and (4) decision approaches. They categorized the applied decision-making techniques of supplier selection problems into MCDMs, MP and artificial intelligence (AI). They also divided the uncertain approaches of solving supplier selection problems into five categories: (1) the fuzzy formulation, (2) probabilistic formulations, (3) formulations with incomplete data (4) formulations with imprecise data and (5) formulations with grey values, through which the fuzzy formulations are the more frequently applied methodology to cope with the uncertainty in supplier selection problem.

Nikghadam et al. (2016) provided a review of solving methodologies for the partner selection problem. According to their research, these could be categorized into three primary classifications: optimization, MCDM, and other methods. As an optimization approach, the partner selection problem is considered to optimize the decision makers' priorities and their stated goals, such as maximizing the customer satisfaction/quality/reliability and minimizing costs/risks. These are just a few of the goals in this area (Jarimo and Salo, 2009; Zhou et al., 2019).

Because of multiple conflicting quantitative and qualitative criteria in partner selection, the MCDM method is a useful methodology to adopt for the problem. As for a MCDM problem, three key issues are to be determined: the determination of affecting criteria, the criteria weights and the prioritization of alternatives which could share the characteristics of the first three stages of the partner selection framework of De Boer et al. (2001). In the literature available on partner selection, the strategic alliance has received much coverage and become an important strategic decision for firms (Inkpen and Ross, 2001). A strategic alliance provides a decision support framework to enable a careful assessment of partners. Today, managers increasingly face the challenge of forming strategic alliances as an inter-organizational co-operation process.

Therefore, some authors have modeled the strategic alliance partner problem as an MCDM problem. Büyüközkan et al. (2008) proposed a hybrid AHP-TOPSIS technique for the selection of the strategic alliance partner in a logistics value chain. Wu et al. (2009)

established an integrated mechanism of the analytic network process (ANP) to introduce both qualitative and quantitative factors affecting the earnings by a company from a strategic alliance. Chen et al. (2011) implemented the fuzzy PROMETHEE technique for information system outsourcing preference in a strategic management problem. Akhavan et al. (2015) proposed a hybrid SWOT-QSPM technique to define the affecting criteria and some MCDM techniques to finally rank the partners. They initially applied the QSPM as a useful tool to prioritize strategies achieved by the SWOT analysis and to improve its output.
Due to the uncertain factors associated with partners' performance which originated from the diversity and complexity of information about partners, the fuzzy version of MCDM techniques has been effectively applied (Büyüközkan and Güleryüz, 2016). Büyüközkan et al. (2017) presented a fuzzy group decision-making approach for customer relationship management (CRM) partner evaluation. They applied fuzzy analytic network process (FANP) for identifying the criteria weights and the fuzzy decision-making trial and evaluation laboratory (F-DEMATEL), to cope with uncertainties of the criteria and to identify the criteria network.

Fu et al. (2019) proposed a comprehensive methodology to select the strategic partners for local tax departments. It includes a new MCDM method with belief structures using the weight learning. They provided a framework for identifying the effective criteria by using two methods including the maximum likelihood estimation and the Hurwicz rule as the learning criterion weights mechanism regarding the data achieved by the partners' comparison and the individual assessments using belief structures.

Based on the literature review, in the following the reasons for proposing the applied methodology are summarized:

1. Why interval valued fuzzy approaches be applied?
   a) In comparison with ordinary fuzzy numbers, the application of IVF datasets to describe and treat imprecise and uncertain factors of the outsourcing problem could serve the purpose better in a more flexible and more general manner, particularly for the problems which are associated with some kind of prediction like selecting the best supplier (Stanujkic, 2015).
   b) The application of IVF sets are less considered in the appropriate literature (Pamucar et al., 2018; Ye, 2010). Besides, application of SWOT and QSPM along with the MCDMs for the partner selection problem within the IVF approach has not been

employed by any previous research so it is the first time that it is proposed for the problem.

2. Why QSPM be applied within the SWOT?

Unlike the benefits of SWOT analysis, there are two main problems which are associated with the large number of strategies generated by this method and its inability to prioritize achieved strategies. As a solution to overcome these disadvantages (so as to find the most important strategies), researchers usually apply weighting methods such as QSPM to determine the weights of criteria, and secondly, to select the major strategies (see Yazdani et al. (2012); Mirzakhani et al. (2014) Cirjevskis and Grasmane (2014); Akhavan et al. (2015) Pazouki et al. (2017) and David et al. (2017).

3. Why MCDMs be applied?

Due to the uncertain factors associated with partners' performance which originates from the diversity and complexity of information about partners, the various versions of MCDM techniques have been effectively applied in this field (Büyüközkan and Güleryüz, 2016). Furthermore, their application is known as one of the most popular approaches for solving the partner selection problem since selecting a supplier is affected by various criteria and sub-criteria, according to which, MCDM techniques could be beneficial. Actually, MCDM has widely gained importance as an evaluation method for the supplier selection problem (Agarwal et al., 2011; Ho et al., 2010; Keshavarz Ghorabaee et al., 2017).

4. Why TOPSIS, COPRAS, ARAS and SAW be applied?

The main goal here is to create as many diverse solutions (ranking of suppliers) as possible. Thus, several MCDM techniques are applied to provide an acceptable solution space. To do so, the authors applied the IVF version of TOPSIS, COPRAS, ARAS and SAW. These techniques are well known and are simple methods with high robustness and high publishing frequencies particularly in management and engineering MCDM problems (Dahooie et al., 2018; Turanoglu Bekar et al., 2016).

5. Why the utility interval estimation method be applied?

It is applied, firstly, as it is a linear programming based method with high accuracy and wide application in various fields to generate an aggregated ranking in group decision situations, and secondly, due to its computational simplicity in computational processing and the ability to determine the preference degrees associated with the rankings generated (Wang et al., 2005).

3. Proposed methodology for strategic alliance partner selection

The perspective of this paper is to propose a practical approach for strategic alliance planning and partner selection in a vague and imprecise environment. The proposed approach is covered by the implementation of three main stages: criteria selection, criteria weighting, and the partner selection.

The first stage, which is mainly related to the definition of the key criteria for partner selection, is obtained using a SWOT analysis and the company motivation through experts' opinions. As mentioned before, the number of resulting strategies from SWOT is too large, and the importance weights of these strategies are not specified. Therefore, QSPM is applied as a prioritizing tool along with Gap analysis to adjust and reduce the number of achieved strategies. The application of QSPM with Gap analysis in the IVF environment is firstly applied in this paper.

The overall methodology and related steps of the paper are described as follows:

Step 1: An IVF-QSPM matrix is applied to find the weights of criteria achieved by SWOT.

Step 2: Gap analysis is applied based on IVF-QSPM to decrease the number of criteria and to select the most important ones.

Step 3: The partners are determined and their decision matrix is constituted based on selected criteria and expert opinions.

Step 4: The partners' performance is measured using IVF-MCDM methods including IVF-TOPSIS, IVF-ARAS, IVF-SAW and IVF-COPRAS (The preliminary formulas related to the interval theory are gathered in step 4).

Step 5: A preference aggregation method is applied by the utility intervals estimation to aggregate the experimental results of proposed methods, and to find the ultimate compound results.

Step 6: The sensitivity of MCDMs to the criteria weights is analyzed and the robustness of proposed MCDM methods is evaluated.

To better guide the reader, the schematic framework of the proposed methodology is represented through figure 1.

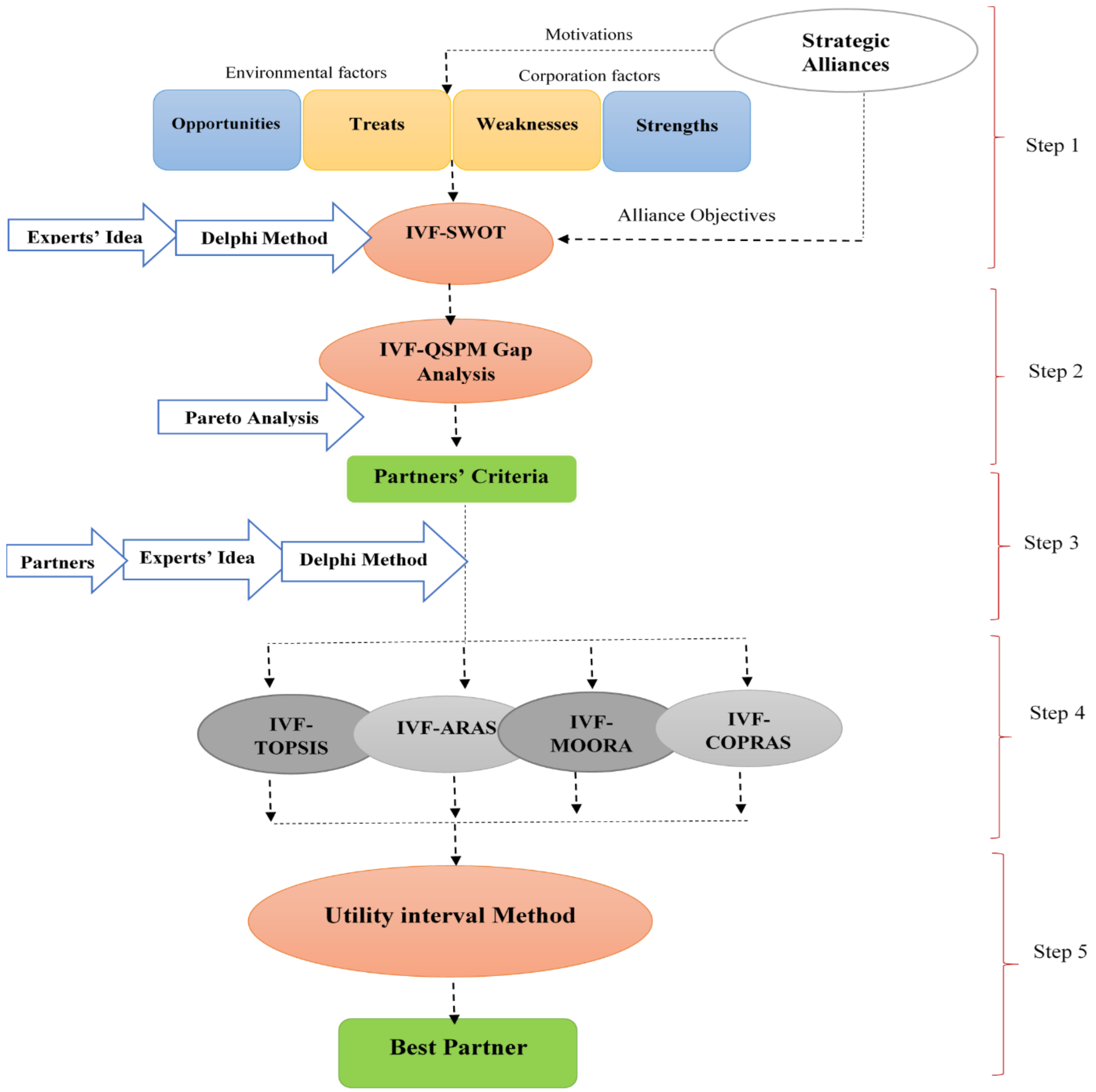


Figure 1. Schematic framework of proposed methodology for strategic alliance of partner selection

Detail explanation of each steps is presented as follow:

Step 1: Application of IVF-SWOT-QSPM

The original version of QSPM is one of the well-known techniques for prioritizing different strategies, mostly achieved from the SWOT method (Dyson, 2004). However, different versions of QSPM have been proposed for different problems, such as the application of fuzzy numbers instead of crisp numbers in QSPM, as well as the implementation of MCDM techniques along with QSPM (Akhavan et al., 2015; Hasan Hosseini Nasab, 2012). Specifically, IVF sets in comparison with triangular fuzzy sets, could share advantages to tackle the complexity relating to outsourcing data which enhances the validity and accuracy of results. To the best of the author's knowledge, the IVF version of QSPM has not been discussed in the literature before. The application of the proposed IVF-QSPM is represented as follows:

Determining the criteria (strategies) interval fuzzy score values according to linguistic variables. These linguistic variables are converted to triangular IVF scores as described in Table 1 based on the IVF conversion scale applied by Vahdani et al. (2012).

Table1. IVF conversion scale for the rating of criteria

score	Linguistic variable	Interval-valued fuzzy number
1	Equal importance (EI)	[(0.05,0.05);0.05 ;(0.15,0.2)]
2	Moderate importance(MI)	[(0.05,0.1);0.15 ;(0.3,0.4)]
3	Strong importance(SI)	[(0.05,0.2);0.35 ;(0.5,0.6)]
4	Very strong importance (VSI)	[(0.3,0.4);0.55 ;(0.7,0.8)]
5	Extreme importance (EI)	[(0.5,0.6);0.75 ;(0.85,1)]

1. Considering $C_i: \left[\left(C_i^a, C_i^{\acute{a}}\right); C_i^b; \left(C_i^{\acute{c}}, C_i^c\right)\right]$ as the interval fuzzy attractiveness score of i^th^ motivation, the normalization operation is applied using Eq. (1) through which, N and $\overline{C_\iota}$ stand for the number of motivations and the normalized attractiveness score of i^th^ motivation. This is a regular normalization way for triangular interval fuzzy numbers in which the lower, middle and upper bound interval numbers are normalized by dividing them into the associated summation of the upper, middle and lower bound numbers of the interval membership in order (Vahdani et al., 2012).

$$\overline{C_\iota} = [\left(\frac{C_i^a}{\sum_{i=1}^N C_i^c}, \frac{C_i^{\acute{a}}}{\sum_{i=1}^N C_i^{\acute{c}}}\right); \frac{C_i^b}{\sum_{i=1}^N C_i^b}; \left(\frac{C_i^{\acute{c}}}{\sum_{i=1}^N C_i^{\acute{a}}}, \frac{C_i^c}{\sum_{i=1}^N C_i^a}\right)] \quad (1)$$

2. Find the normalized criteria score by using Eq. (2)

$$\hat{y}_{ij}^p = \bar{C}_i^p \times y_{ij}^p, \qquad p \in (a, \acute{a}, b, \acute{c}, c), i = 1,2, \dots N, \qquad j = 1,2, \dots J \quad (2)$$

where j is the number of criteria, y_{ij} represents the interval fuzzy score of i^th^ motivation (S,W, O, T) for j^th^ criterion (strategies)

3. Computing the total criteria score by applying Eq.(3)

$$TS_j^p = \sqrt[N]{\prod_{i=1}^N \hat{y}_{ij}^p}, p \in (a, \acute{a}, b, \acute{c}, c), i = 1,2, \dots N, \qquad j = 1,2, \dots . J \quad (3)$$

4. Finding the feasibility degree of each criterion (F_j). The feasibility degree is achieved according to the structured group of experts' opinions and through the Delphi method as a

well-known communication technique (Rowe and Wright, 1999). In this way, the experts are asked about the possibility of applying each strategy (criteria) in two or more rounds. The answers are given based on the company capabilities for implementing the strategies and the potential possibility of the strategies to improve the company's current technical and economic situation. By collecting the answers in the first round and in the second round, the experts revise their previous answers with regard to the other members' answers on their panel. This process will be continued for several rounds until the answer ranges converge to a common one. The final grade of the last round is assumed as the feasibility degree of each criterion (F_j).

5. Computing the final weight of the criteria score (W_j) by multiplying the total criterion score to its feasibility degree.

$$W_j^p = TS_j^p \times F_j \,, \qquad p \in (a, \acute{a}, b, \acute{c}, c), i = 1,2, \dots N \tag{4}$$

Step2: Application of Gap Analysis

The Gap analysis will be applied at this stage in order to reduce the number of strategies (criteria) concluded from the SWOT analysis. In this step, it should be highlighted that an estimation of Pareto analysis is applied to find the top portion of effective criteria. Under a Pareto analysis, it is believed that 20% of the reasons determine 80% of the problem which is called the 80/20 rule. In the given illustrative application, we found that 30% of the criteria achieved more than 70% of the cumulative weight, therefore the authors solved the problem under the 70/30 rule. To do so, the top 30% criteria which achieve more than 70% of the total cumulative weights ($\sum_j W_j$), will be taken into consideration while the rest, which includes less than 30% of the total cumulative weight, can be neglected.

Therefore, the paired comparison will be applied to intervals obtained for each criterion. In this step of the proposed model, we develop a transitive order relating to the fuzzy intervals in order to explain the ranking between any two intervals according to Sengupta and Pal (2000), as explained below:

1. Let $C_i\colon \left[\left(C_i^a, C_i^{\acute{a}}\right); C_i^b; \left(C_i^{\acute{c}}, C_i^c\right)\right]$ and $C_j\colon \left[\left(C_j^a, C_j^{\acute{a}}\right); C_j^b; \left(C_j^{\acute{c}}, C_j^c\right)\right]$ be two candidate criteria, the acceptability function of $C_i < C_j$ which is called A_{ij}, would be defined as below:

$$A_{ij} = v((C_i) \leq (C_j)) = \begin{cases} 0 & if\ h(C_i) \geq h(C_j) \\ 0 < R_{ij} < 1 & if\ h(C_i) < h(C_j)\ and\ C_i^c > C_j^a \\ 1 & if\ h(C_i) < h(C_j)\ and\ C_i^c < C_j^a \end{cases} \tag{5}$$

where A_{ij} is calculated by Eq. (6)

$$A_{ij} = \frac{h(C_j) - h(C_i)}{m(C_j) + m(C_i)} \tag{6}$$

Here, $h(C_j)$ represents the interval mean (according to definition 4) and $m(C_j)$ stands for the central point of interval relating to C_j (criteria j) with Eqs. (7) to (9):

$$m(C_j) = \frac{m_j^U - m_j^L}{2} \tag{7}$$

$$m_j^L = \frac{C_j^a + C_j^{á}}{2} \tag{8}$$

$$m_j^U = \frac{C_j^{ć} + C_j^c}{2} \tag{9}$$

m_j^L and m_j^U represent the central point of the lower bound and upper bound respectively.

2. For $i \neq j$ and $j = 1, 2, \ldots N,$ the Gap weight GW_j, is considered as $GW_j = \min(v(C_i \geq C_j))$, then the total weighted Gap (TGW_j) and the weighted normalized Gap (NGW_j) of any criteria are achieved through Eqs.(10) to (12):

$$GW_j = \min_i(A_{ij}) \tag{10}$$

$$TGW_j = \sum_{j=1}^{N} \mathrm{GW}_j \tag{11}$$

$$NGW_j = \frac{GW_j}{TGW_j} \tag{12}$$

The criteria with more NGW_j are considered as more significant ones which should be paid the most attention. In this step, according to experts' opinions, the criteria with more NGW_j the sum of which exceeds 70% of total cumulative weights, will be selected as the key criteria, and the rest can be ignored.

Step 3: Determine the partners and constitute the partners' decision matrix based on selected criteria and expert opinions

By evaluating the criteria in the previous step, which resulted in the determination of the most significant criteria, several appropriate partners for a strategic alliance are taken into consideration for investigation based on selected criteria. All the available alternatives or partners will be qualified by experts of the partner selection committee and according to the selected criteria. Initially the committee invites the interested organizations (existing or new partners) to express their interests in implementing a specific project through issuing a call for expression of interest. This call informs interested partners on the project goals and specifications; criteria for selection; deadlines for submission of interest; date of selection decision; and other particularities of the operations. Then, the partners can bring forward initiatives by submitting a concept note to the relevant project. The committee is required to check whether the applicant organization meets the basic compatibility/eligibility criteria for establishing partnership as the initial qualification as an initial filtering. Finally, the committee provides the list of all eligible applicant partners to carry out the main qualification process based on the criteria selected in the previous step and with regard to linguistic variables for the rating of criteria given in Table 1. The output of this step addresses the interval-valued decision matrix being inserted as the input data for application of MCDM techniques. To form the decision matrix, again the Delphi method is performed and the group of experts are asked to score the eligible applicant partners based on selected criteria.

Step 4: Application of IVF-MCDMs for the partner selection problem

In this step of the proposed model, IVF-MCDM such as IVF-TOPSIS, IVF-ARAS, IVF-SAW and IVF- COPRAS, are implemented to investigate the partners' performance in order to specify the best one. It is worth noting that the obtained IVF weights of criteria will be considered as one of the inputs for the implemented MCDMs.

Step 4.1. IVF sets

The necessary definitions of IVF sets, in terms of six definitions, are addressed in here.

Definition 1. An IVF set on $(-\infty,+\infty)$ based on Gorzałczany (1987) is introduced as:

$$A=\left\{\left(x,\left[\mu_A^L(x),\mu_A^U(x)\right]\right)\right\} \tag{13}$$

$$\mu_A^L(x),\mu_A^U(x):X\rightarrow[0,1]\ \forall x\in X,\ \ \mu_A^L(x)\le\mu_A^U(x)$$

$$\bar{\mu}_A(x)=\left[\mu_A^L(x),\mu_A^U(x)\right]$$

$$A=\{(x,\bar{\mu}_A(x))\},\quad x\in(-\infty,+\infty)$$

Where $\mu_A^L(x)$ and $\mu_A^U(x)$ correspond to the lower and upper limit of membership.

Definition 2. Let *M* be $N_x=[N_x^-;N_x^+]$ and *v* be a positive non-fuzzy number,

$$v\times M(x.y)=[v.M_y^-;v.M_y^+] \tag{14}$$

Definition3. Let $N=[(\mathrm{N}_1,\mathrm{N}_1^{'});\mathrm{N}_2;(\mathrm{N}_3^{'},\mathrm{N}_3)]$ and $\tilde{M}=[(\mathrm{M}_1,\mathrm{M}_1');\mathrm{M}_2;(\mathrm{M}_3',\mathrm{M}_3)]$ be two triangular interval fuzzy numbers, then the subtraction, division, summation and multiplication operations between them could be given as:

$$\tilde{N} - \tilde{M} = [(N_1, N_1'); N_2; (N_3', N_3)] - [(M_1, M_1'); M_2; (M_3', M_3)] = \tag{15}$$

$$[(N_1 - M_3, N_1' - M_3'); N_2 - M_2; (N_3' - M_1', N_3 - M_1)]$$

$$\tilde{N} \div \tilde{M} = [(N_1, N_1'); N_2; (N_3', N_3)] \div [(M_1, M_1'); M_2; (M_3', M_3)] = \tag{16}$$

$$[(N_1 \div M_3, N_1' \div M_3'); N_2 \div M_2; (N_3' \div M_1', N_3 \div M_1)]$$

$$\tilde{N} * \tilde{M} = [(N_1, N_1'); N_2; (N_3', N_3)] + [(M_1, M_1'); M_2; (M_3', M_3)] \quad * \in (+, \times) \tag{17}$$

Definition 4. We say that $\tilde{N} \geq \tilde{M}$ if $h(\tilde{N}) \geq h(\tilde{M})$ is where

$$h(\tilde{N}) = \frac{N_1 + N_1' + 2N_2 + N_3' + N_3}{6} \tag{18}$$

$$h(\tilde{M}) = \frac{M_1 + M_1' + 2M_2 + M_3' + M_3}{6} \tag{19}$$

Definition 5. The intersection of two IVFs could be found as the minimum of their respective lower and upper bounds of their membership intervals. Considering any two intervals as $N_x = [N_x^-; N_x^+] \subset [0,1]$ and $M_y = [M_y^-; M_y^+] \subset [0,1]$, the minimum of both intervals is given as *k*:

$$K = MIN(N_x, M_y) = [MIN(N_x^-, M_y^-).MIN(N_x^+, M_y^+)] \tag{20}$$

Definition 6. Likewise, the union of two IVFs could be defined as the maximum of their respective lower and upper bounds of their membership intervals:

$$K = MAX(N_x, M_y) = [MAX(N_x^-, M_y^-).MAX(N_x^+, M_y^+)] \tag{21}$$

$$= [(N_1 * M_1, N_1' * M_1'); N_2 * M_2; (N_3' * M_3', N_3 * M_3)]$$

Step 4.2. IVF-TOPSIS

In this paper, an IVF-TOPSIS method is applied to investigate the partners' performance and to select the best partner(s).

The proposed method is concerned with the concepts of the positive ideal and negative ideal solutions to solve MCDM problems in an IVF environment. The concept of fuzzy TOPSIS was proposed by Chen (2000). Various applications of it have been implemented by Ashtiani et al. (2009); (Mokhtarian et al., 2014); Pires et al. (2011); (Yue and Yue, 2019).

To specify the procedure of the proposed IVF-TOPSIS, a set of *m* alternatives $(A_1, A_2, \ldots A_m)$ evaluated with respect to *n* criteria $(C_1, C_2, \ldots C_n)$ with a relative weight of $(W_1, W_2, \ldots W_n)$, should be considered. It should be noted that in this study, all the studied criteria are associated with benefit strategies and considered as positive criteria. Let $X = (x_{ij})_{m\times n}$be the decision matrix, then the proposed IVF-TOPSIS can be summarized as follows:

1. Given $\widetilde{x}_{ij}: \left[\left(x_{ij}^{a}, x_{ij}^{\acute{a}}\right); x_{ij}^{b}; \left(x_{ij}^{\acute{c}}, x_{ij}^{c}\right)\right]$as the IVF score of j[th] criteria from i[th] decision maker's point of view, the normalization of decision matrix $X = (x_{ij})_{m\times n}$ is applied using the following Eq. (22) in which x_j^{c+} represents the maximum value of the upper values of the triangular membership function within the j[th] criteria.

$$\tilde{n}_{ij} = \left[\left(\frac{x_{ij}^{a}}{x_j^{c+}}, \frac{x_{ij}^{\acute{a}}}{x_j^{c+}}\right); \frac{x_{ij}^{b}}{x_j^{c+}}; \left(\frac{x_{ij}^{\acute{c}}}{x_j^{c+}}, \frac{x_{ij}^{c}}{x_j^{c+}}\right)\right] \quad (22)$$

2. Find the weighted normalized matrix, $\tilde{V} = [\tilde{v}_{ij}]_{n\times m}$, by multiplying the criteria weights (obtained from Eq. (4)) against the normalized decision matrix regarding Eq. (17), given in Eq. (23).

$$\tilde{v}_{ij} = \widetilde{w}_j \times \tilde{n}_{ij} \quad (23)$$

For the sake of integration and simplicity of comparisons between applied MCDM methods, obtaining the normalized decision matrix and the weighted normalized decision matrix in all the applied MCDM methods, follows the same procedure.

3. Determine the positive ideal (A^{+}) and negative ideal (A^{-}) solutions as most preferable and least preferable alternatives in order. This procedure will be applied according to Eqs. (24) and (25).

$$A^{+} = \widetilde{(v_1^{+}}, \ldots, \tilde{v}_n^{+}) = max_i \tilde{v}_{ij} \quad (24)$$

$$A^{-} = \widetilde{(v_1^{-}}, \ldots, \tilde{v}_n^{-}) = min_i \tilde{v}_{ij} \quad (25)$$

4. Compute the ideal distance matrix (D^{+}) with respect to definition A.1 which is given in Eqs. (26) to (28).

$$D^{+} = \begin{bmatrix} \left|\tilde{v}_{11} - \tilde{v}_1^{+}\right| & \cdots & \left|\tilde{v}_{1n} - \tilde{v}_n^{+}\right| \\ \vdots & \ddots & \vdots \\ \left|\tilde{v}_{m1} - \tilde{v}_1^{+}\right| & \cdots & \left|\tilde{v}_{nn} - \tilde{v}_n^{+}\right| \end{bmatrix} \quad (26)$$

$$D^{+} = [d_{ij}^{p+}] = \begin{bmatrix} \left(v_{11}^{a}, v_{11}^{\acute{a}}\right); v_{11}^{b}; \left(v_{11}^{\acute{c}}, v_{11}^{c}\right) - \left(v_{11}^{a+}, v_{11}^{\acute{a}+}\right); v_{11}^{b+}; \left(v_{11}^{\acute{c}+}, v_{11}^{c+}\right) & \cdots & \left(v_{1n}^{a}, v_{1n}^{\acute{a}}\right); v_{1n}^{b}; \left(v_{1n}^{\acute{c}}, v_{1n}^{c}\right) - \left(v_{1n}^{a+}, v_{1n}^{\acute{a}+}\right); v_{1n}^{b+}; \left(v_{1n}^{\acute{c}+}, v_{1n}^{c+}\right) \\ \vdots & \ddots & \vdots \\ \left(v_{m1}^{a}, v_{m1}^{\acute{a}}\right); v_{m1}^{b}; \left(v_{m1}^{\acute{c}}, v_{m1}^{c}\right) - \left(v_{m1}^{a+}, v_{m1}^{\acute{a}+}\right); v_{m1}^{b+}; \left(v_{m1}^{\acute{c}+}, v_{m1}^{c+}\right) & \cdots & \left(v_{mn}^{a}, v_{mn}^{\acute{a}}\right); v_{mn}^{b}; \left(v_{mn}^{\acute{c}}, v_{mn}^{c}\right) - \left(v_{mn}^{a+}, v_{mn}^{\acute{a}+}\right); v_{mn}^{b+}; \left(v_{mn}^{\acute{c}+}, v_{mn}^{c+}\right) \end{bmatrix} \quad (27)$$

$$[d_{ij}^{p+}] = \begin{bmatrix} \left(d_{11}^{a+}, d_{11}^{\acute{a}+}\right); d_{11}^{b+}; \left(d_{11}^{\acute{c}+}, v_{11}^{c+}\right) & \cdots & \left(d_{1n}^{a+}, v_{1n}^{\acute{a}+}\right); d_{1n}^{b+}; \left(d_{1n}^{\acute{c}+}, d_{1n}^{c+}\right) \\ \vdots & \ddots & \vdots \\ \left(d_{m1}^{a+}, d_{m1}^{\acute{a}+}\right); d_{m1}^{b+}; \left(d_{m1}^{\acute{c}+}, d_{m1}^{c+}\right) & \cdots & \left(d_{mn}^{a+}, d_{mn}^{\acute{a}+}\right); d_{mn}^{b+}; \left(d_{mn}^{\acute{c}+}, d_{mn}^{c+}\right) \end{bmatrix} p\epsilon(a, \acute{a}, b, \acute{c}, c) \quad (28)$$

5. Compute the anti-ideal distance matrix (D^{-}) with respect to definition A.1 which is given in Eqs. (29) to (33).

$$D^{-} = \begin{bmatrix} |\tilde{v}_{11} - \tilde{v}_{1}^{-}| & \cdots & |\tilde{v}_{1n} - \tilde{v}_{n}^{-}| \\ \vdots & \ddots & \vdots \\ |\tilde{v}_{m1} - \tilde{v}_{1}^{-}| & \cdots & |\tilde{v}_{nn} - \tilde{v}_{n}^{-}| \end{bmatrix} = \begin{bmatrix} d_{11}^{-} & \cdots & d_{1n}^{-} \\ \vdots & \ddots & \vdots \\ d_{m1}^{-} & \cdots & d_{mn}^{-} \end{bmatrix} \quad (29)$$

$$[d_{ij}^{p-}] = \begin{bmatrix} (v_{11}^{a}, v_{11}^{\acute{a}}); v_{11}^{b}; (v_{11}^{\acute{c}}, v_{11}^{c}) - (v_{11}^{a-}, v_{11}^{\acute{a}-}); v_{11}^{b-}; (v_{11}^{\acute{c}-}, v_{11}^{c-}) & \cdots & (v_{1n}^{a}, v_{1n}^{\acute{a}}); v_{1n}^{b}; (v_{1n}^{\acute{c}}, v_{1n}^{c}) - (v_{1n}^{a-}, v_{1n}^{\acute{a}-}); v_{1n}^{b-}; (v_{1n}^{\acute{c}-}, v_{1n}^{c-}) \\ \vdots & \ddots & \vdots \\ (v_{m1}^{a}, v_{m1}^{\acute{a}}); v_{m1}^{b}; (v_{m1}^{\acute{c}}, v_{m1}^{c}) - (v_{m1}^{a-}, v_{m1}^{a\acute{-}}); v_{m1}^{b-}; (v_{m1}^{c\acute{-}}, v_{m1}^{c-}) & \cdots & (v_{mn}^{a}, v_{mn}^{\acute{a}}); v_{mn}^{b}; (v_{mn}^{\acute{c}}, v_{mn}^{c}) - (v_{mn}^{a-}, v_{mn}^{a\acute{-}}); v_{mn}^{b-}; (v_{mn}^{\acute{c}-}, v_{mn}^{c-}) \end{bmatrix} \quad (30)$$

$$[d_{ij}^{p-}] = \begin{bmatrix} (d_{11}^{a-}, d_{11}^{\acute{a}-}); d_{11}^{b-}; (d_{11}^{\acute{c}-}, d_{11}^{c-}) & \cdots & (d_{1n}^{a-}, v_{1n}^{a\acute{-}}); d_{1n}^{b-}; (d_{1n}^{\acute{c}-}, d_{1n}^{c-}) \\ \vdots & \ddots & \vdots \\ (d_{m1}^{a-}, d_{m1}^{a\acute{-}}); d_{m1}^{b-}; (d_{m1}^{c\acute{-}}, d_{m1}^{c-}) & \cdots & (d_{mn}^{a-}, d_{mn}^{\acute{a}-}); d_{mn}^{b-}; (d_{mn}^{c\acute{-}}, d_{mn}^{c-}) \end{bmatrix} \; p\epsilon(a, a\acute{,} b, c, \acute{c}) \quad (31)$$

6. Compute the cumulative ideal and anti-ideal distances in Eqs. (23) and (24).

$$d_{i}^{p-} = \sum_{j=1}^{n} d_{ij}^{p-} \quad p\epsilon(a, a\acute{,} b, c, \acute{c}) \quad (32)$$

$$d_{i}^{p+} = \sum_{j=1}^{n} d_{ij}^{p+} \quad p\epsilon(a, a\acute{,} b, c, \acute{c}) \quad (33)$$

7. Find the closeness index (CL_{i}^{p}) using Eq. (34).

$$[CL_{i}^{p}] = \frac{d_{i}^{p-}}{d_{i}^{p-} + d_{i}^{p+}} \quad p\epsilon(a, a\acute{,} b, c, \acute{c}) \quad (34)$$

8. Find the collective closeness index for each alternative (CI_i) using definition 4.

9. Rank the alternatives consideringCI_i .

Step 4.3. IVF-ARAS

The ARAS method was introduced by Zavadskas and Turskis (2010) to solve different optimization problems. The following steps describe the proposed IVF-ARAS:

1. Find the maximum value of the criteria in the decision matrix for the lower, middle and upper values of the triangular membership function (x_{0j}^{p}), as the first row of the decision matrix (Eqs. (35) and (36)).

$$x_{0j}^{p} = \max(x_{ij}^{p}) \, p\epsilon(a, a\acute{,} b, c, \acute{c}) \quad (35)$$

$$X = \begin{bmatrix} (x_{01}^{a}, x_{01}^{\acute{a}}); x_{01}^{b}; (x_{01}^{\acute{c}}, x_{01}^{c}) & \dots & (x_{0n}^{a}, x_{0n}^{\acute{a}}); x_{0n}^{b}; (x_{0n}^{\acute{c}}, x_{0n}^{c}) \\ (x_{11}^{a}, x_{01}^{\acute{a}}); x_{11}^{b}; (x_{11}^{\acute{c}}, x_{11}^{c}) & \dots & (x_{1n}^{a}, x_{0n}^{\acute{a}}); x_{1n}^{b}; (x_{1n}^{\acute{c}}, x_{1n}^{c}) \\ \vdots & \ddots & \vdots \\ (x_{m1}^{a}, x_{m1}^{\acute{a}}); x_{m1}^{b}; (x_{m1}^{\acute{c}}, x_{m1}^{c}) & \cdots & (x_{mn}^{a}, x_{mn}^{\acute{a}}); x_{mn}^{b}; (x_{mn}^{\acute{c}}, x_{mn}^{c}) \end{bmatrix} \quad (36)$$

2. Normalize the decision matrix (X) and determine the weighted normalized decision matrix (*v*) according to *step 1* and *step 2* of the TOPSIS method (Eqs. (22) and (23)).
3. Find the values of the optimality function by following Eq. (37). Therefore, the greater the value of the optimality function $\widetilde{S_i}$, the more effective the alternative will be.

$$\widetilde{S}_i = s_i^p = \sum_{j=1}^{n} v_{ij}^p \qquad p \in (a,'a,b,c',c) \tag{37}$$

4. Determine the priorities of alternatives with respect to the value of $\widetilde{S_i}$, which should be converted to a crisp number by computing the mean of the interval given in definition 4.
5. Compute the degree of the alternative utility by comparing the variant which is analyzed with the most ideal one S_0. The equation used for the calculation of the utility degree of an alternative (A_i) is given below, in which S_i and S_0 are the optimal criterion values obtained from Eq. (38).

$$K_i = \frac{S_i}{S_0} \qquad i = 1, 2, \ldots, m \tag{38}$$

6. Rank the alternatives $(\mathrm{A}_1, \mathrm{A}_2, \ldots\ \mathrm{A}_\mathrm{m})$ with respect to the calculated values of k_i.

Step 4.4. IVF-SAW

This method was initially proposed by Churchman and Ackoff (1954), to decide on a portfolio selection problem. The biggest advantage of the SAW method and why it is widely applied is its simplicity and ease of use. Its application in partner selection has recently been investigated by (Yang et al., 2008); Zavadskas et al. (2010). The procedure of SAW can be summarized as follows:

1. Calculate the normalized and weighted normalized decision matrix as described in *step 1* and *step 2* of IVF-TOPSIS.
2. Calculate the total ratings for each alternative, as given in Eq. (37).
3. Compute a crisp value for each total score using definition 4.
4. Select the alternative(s) with the maximum total score (Si).

Step 4.5. IVF-COPRAS

The conventional COPRAS method that was initially proposed by Zavadskas et al. (2001), determines the proportional and direct dependence of significance and priority of alternatives according to the criteria. Vahdani et al. (2014) proposed the IVF-COPRAS for the robot selection problem. It was then applied in a wide range of MCDM problems (Antucheviciene et al., 2015; Ghorabaee et al., 2017; Turanoglu Bekar et al., 2016).

The mathematical concept of IVF-COPRAS is as follows:

1. Construct the normalized and weighted normalized IVF decision matrix with respect to *step 1* and *step 2* of IVF-TOPSIS.
2. Calculate the sums of beneficial criteria values ($\tilde{p}_i$) according to formula (38). The larger value of ($\tilde{p}_i$)for benefit criteria is preferable.

$$\tilde{p}_i = p_i^p = \sum_{j=1}^{n} v_{ij}^p \quad p \in (a, a', b, c', c) \tag{38}$$

3. Compute the relative weight of each alternative ($\widetilde{Q_i}$). As we have no negative criteria, the sum $\widetilde{\mathrm{R}}_{\mathrm{i}}$ of criteria equals zero, therefore, the relative weight of alternatives is computed through the values of $\tilde{p}_i$ and by applying definition
4. The alternatives with higher values of $\widetilde{Q_i}$stand for a more satisfying alternative.
5. Find the utility degree of each alternative (N_i) by formula (39), where $\widetilde{\mathrm{Q}}_{\max}$ corresponds to the highest satisfaction degree among the alternatives.

$$N_i = \frac{h(\widetilde{Q}_i)}{\widetilde{Q}_{max}} \times 100\% \qquad i = (1, 2, \ldots, n) \tag{39}$$

6. Rank the alternatives with regard to the utility degree (N_i).

Step 5: Application of a preference aggregation method by the utility intervals

The use of a single MCDM method for prioritization cannot ensure a robust approach (Akhavan et al., 2015). Particularly when the differences between the alternatives are inherently close together or when the number of alternatives increases, the necessity for a robust aggregation method increases (Varmazyar et al., 2016). Between the aggregation methods, the utility interval is implemented in this paper because of this approach flexibility and dealing with different levels of uncertainty.

Step 6: Analyzing the sensitivity of MCDMs to the changes occurred in criteria weight

Finally, the sensitivity analysis is applied to identify how sensitive the MCDMs are to the criteria weight and to find the most robust method based on the sensitivity coefficient.

4. Pilot application: Strategic alliance planning for partner selection in a holding car manufacturer company

A strategic alliance, as an inter-organizational co-operation process, plays an essential role in reducing costs while increasing the production quality in car industries. Forming strategic alliances provides a good opportunity for car manufacturers to extend their resources and strengthen their partners' capabilities and potentials. Furthermore, receiving the specialized knowledge, technology and operational platforms from external providers or partners, besides sharing the risks of supplying processes, could result in various advantages. Some of these include reducing staffing levels, providing efficient procurement services and developing new markets. The case study of this paper focuses on a heavy machinery producer in Iran namely SH.KH, which works with casting units and the production of cranks. The company aims to succeed in the Middle Eastern market of heavy machinery of cargo and passenger carriages. For this reason, the application of contracts with appropriate enterprises can be beneficial for the company.

4.1. Defining criteria and calculating criteria weights

The required case study for implementation of the proposed methodology is taken from the research presented by Akhavan et al. (2015) which attained the SH.KH car manufacturing company strategies based on a SWOT analysis (note that due to the privacy regarding the company information, its full name cannot be stated here).The current analysis is provided by a survey completed by experts at the company and the managerial committee of the Iranian Ministry of Mining and Industry within which, the criteria and motivations of the company with its partners are determined. In the current research, we aim to develop the IVF version of QSPM for SH.KH and select the most appropriate partner within the IVF-MCDM algorithms. The company's strategies attained from SWOT are introduced in Table 2.

Table 2. SWOT analysis

Internal Factors	
Weaknesses: 1. Lack of appropriate mechanism in order to prepare pieces in the country. 2. Old-age production equipment. 3. Existence of pooling production system or make to a stock production system. 4. Lack of a planned marketing policy in national and international markets. 5. Low number of delegation within the country. 5. Lack of information on new prices. 6. Lack of mechanized logistic operations (e.g. lack of lift trucks). 7. Existence of space and technology restrictions. 8. Low investment power due to high investment in importing foreign pieces. 9. Weakness in maintenance management processes (lack of a mechanized system and low specialty of human resources). 10. Weak information flow among different departments of company.	Strengths: 1. Possibility of human outsourcing. 2. Remarkable scientific power in performing research and development projects. 3. Establishment of internal network system and capability of its promotion. 4. Establishment of customer representative in the company. 5. Existence of acceptable educational facilities. 6. Good production flexibility. 7. Belief in ascendency and quality of services and try to get quality management standard in the company services. 8. Company ability to apply exemptions of customs tariff in importing spare parts.

External Factors	
Opportunities: 1. Government supporting policies for renovation and expansion of public transportation. 2. Customs administration discounts for importing parts. 3. Using valid and new brands. 4. Government supporting policies for increasing export rate. 5. Increasing attention to environment and decreasing fuel consumption. 6. Increasing rate of population and city immigration. 7. 13th note of Iranian policy in 2010 for Budget Act. 8. Government supporting policies for privatization. 9. Existence of good banking facilities and foreign exchange reserves. 10. Application of novel advanced technologies for engine production.	Threats: 1. Government restrictions in importing pieces from foreign countries. 2. Rapid changes in technology of car industry in a global context. 3. Economic sanction that decreases the speed of technology transfer. 4. Import of buses by the government. 5. Necessity of observing strict environmental rules. 6. Rapid following of advanced world technologies by competitors. 7. Customs administration of importing cars. 8. Changing attitude towards luxury-oriented and private car ownership. 9. Globalization.
Strategies	
WO criteria 1. Having automotive systems for producing high volume products. 2. Having guidance costs of major production processes in order to increase competing power. 3. Ability to re-engineer after-sales services. 4. Establishing up-to-date management methods. 5. Ability of equipment renovation to increase production capacity. 6. Ability to create a network of diverse and dispersing internal and external selling centers.	SO criteria 1. Ability to increase production capacity. 2. Diversify selling processes via expansion of export and new products. 3. Help to increase marketing power to have effective attendance in the regional markets. 4. Expanding productivity and incentive systems. 5. Having a relationship with other industries and expanding industrial marketing activities.
WT criteria 1. Attaining a trade partner in order to get access to new technologies. 2. Re-engineering organizational structures and relations. 3 Utilizing the capacity of other manufacturers to expand services to suppliers. 4.Creating specialized productive manufacturing units with flexible technological capability, to increase the expected variety of products.	ST criteria 1. Possessing a big network of suppliers. 2. Internal (within the country) supplying of pieces. 3. Having a good partnership with global network of suppliers. 4. Diverse production of special cars and public city transportation cars with respect to available technology within the company. 5. Having an optimized supply chain management of human resource.

By defining the company strategies through the SWOT analysis, the following procedures are done:

1- Initially the attractiveness scores of motivations (S, W, O, T) represented in table 2 are distinguished using IVF scores and according to a group of 10 experts applying the Delphi procedure. The experts are asked to fill in the data. A part of the original data of this step is illustrated in Table 3. The resulting IVF-values (see Table 1 for interval values) of this step will be then normalized by applying Eq. (1), and are then called normalized weights of motivations.

Table 3. A part of the original data for determining the attractiveness scores of motivations achieved from the Delphi procedure

motivations	attractiveness scores	IVF-values					Normalized weights of motivations				
		a	a’	b	c’	c					
O_1	EI	0.5	0.6	0.75	0.85	1	0.017	0.024	0.038	0.059	0.097
O_2	EI	0.5	0.6	0.75	0.85	1	0.017	0.024	0.038	0.059	0.097
O_3	SI	0.05	0.2	0.35	0.5	0.6	0.002	0.008	0.018	0.035	0.058
…….	…….	…..	….	…..	…..	….	…….	…….	…….	…….	…….

2- The IVF scores of criteria (strategies) with respect to motivations are then determined here. The feasibility degree of criteria is also defined in this step, based on experts' opinion and through the Delphi method. A part of the original QSPM data of this step is given in Table 4.

Table 4. A part of original IVF scores of criteria (strategies) with respect to motivations achieved from the Delphi procedure

motivations	criteria							
	SO_1	SO_2	SO_3	SO_4	SO_5	WO_1	WO_2	…..
O_1	VSI	EI	VSI	SI	VSI	VSI	VSI	…..
O_2	EI	EI	MI	VSI	SI	VSI	EI	…..
O_3	SI	SI	MI	VSI	VSI	MI	SI	…..
…….	…….	…….	…….	…….	…….	…….	…….	…..

3- The criteria scores achieved by table 4 are then multiplied to normalized weights of motivations using Eq.(2).

4- Then the total criteria score is computed due to Eq.(3).

5- The final weight of the criteria score (W_j) is computed by multiplying the total criterion score to its feasibility degree, F_j. In Table 5 the total criteria score and the feasibility degree of criteria is represented.

Table 5. Feasibility degree and total score for criteria

criteria	Total criteria score (TS_j)					Feasibility degree (F_j)
	a	a'	b	c'	c	
SO_1	0.00300	0.00700	0.01467	0.02733	0.04667	3
SO_2	0.00125	0.00475	0.01200	0.03775	0.07275	4
SO_3	0.00100	0.00300	0.00900	0.02300	0.04500	1
SO_4	0.00150	0.00525	0.01325	0.03025	0.05775	4
SO_5	0.00100	0.00380	0.01680	0.02520	0.04940	5

WO_1	0.00050	0.00300	0.00800	0.02150	0.04300	2
WO_2	0.00125	0.00475	0.01250	0.02900	0.05575	4
WO_3	0.00100	0.00300	0.00800	0.02100	0.04300	1
WO_4	0.00150	0.00500	0.01275	0.02925	0.05625	4
WO_5	0.00067	0.00333	0.00867	0.02300	0.04567	3
WO_6	0.00067	0.00333	0.00900	0.02333	0.04567	3
ST_1	0.00050	0.00250	0.00700	0.02000	0.04100	2
ST_2	0.00100	0.00400	0.01000	0.02400	0.04800	1
ST_3	0.00050	0.00250	0.00650	0.01900	0.03900	2
ST_4	0.00000	0.00100	0.00350	0.00950	0.01950	2
ST_5	0.00125	0.00425	0.01150	0.02750	0.05250	4
WT_1	0.00100	0.00300	0.00750	0.02100	0.04250	2
WT_2	0.00050	0.00250	0.00700	0.01950	0.04000	2
WT_3	0.00100	0.00400	0.01000	0.02500	0.04900	1
WT_4	0.00312	0.00722	0.01108	0.01567	0.01853	4

6- In the next step, the final weight of the criteria score (W_j) based on Eq. (4) is computed. To do so, the total criteria scores (TS_j) are multiplied to feasibility degree (F_j) (see Table 6).

7- Apply the QSPM-Gap analysis. To do so, the central point of the lower bound (m_j^L), the central point of the upper bound (m_j^U), and consequently the central point (m_j), as well as the mean of the interval (h_j) (see definition 4) corresponding to the criteria, are computed according to Eqs. (7) to (10), as demonstrated in Table 6. In order to reduce the number of criteria achieved and to find the most significant criteria, Gap analysis is applied for the QSPM outputs. To enable this, paired comparisons are done between criteria to compute the acceptability function of $C_i < C_j$ according to Eqs. (5) and (6). Table 7 reflects the output of IVF- QSPM obtained with Gap analysis. Computational results of the final step of Gap analysis including gaining the Gap weight (GW_j), weighted normalized Gap (NGW_j), and the ultimate rankings are reported in the last three rows of Table 7.

Table 6. Final weight, lower, upper and central points, and the mean of interval for the criteria score

criteria	Final weight of criteria score (W_j)					m_j^L	m_j^U	m_j	h_j
	a	a'	b	c'	c				
SO_1	0.009	0.021	0.044	0.082	0.140	0.0150	0.1110	0.0480	0.0567
SO_2	0.005	0.019	0.048	0.151	0.291	0.0121	0.2214	0.1046	0.0939
SO_3	0.001	0.003	0.009	0.023	0.045	0.0019	0.0340	0.0160	0.0148
SO_4	0.006	0.021	0.053	0.121	0.231	0.0135	0.1760	0.0812	0.0809
SO_5	0.005	0.019	0.084	0.126	0.247	0.0122	0.1867	0.0872	0.0942
WO_1	0.001	0.006	0.016	0.043	0.086	0.0036	0.0641	0.0303	0.0278
WO_2	0.005	0.019	0.050	0.116	0.223	0.0123	0.1697	0.0787	0.0773
WO_3	0.001	0.003	0.008	0.021	0.043	0.0017	0.0322	0.0152	0.0139
WO_4	0.006	0.020	0.051	0.117	0.225	0.0127	0.1711	0.0792	0.0781
WO_5	0.002	0.010	0.026	0.069	0.137	0.0059	0.1027	0.0484	0.0449
WO_6	0.002	0.010	0.027	0.070	0.137	0.0058	0.1035	0.0489	0.0454
ST_1	0.001	0.005	0.014	0.040	0.082	0.0032	0.0610	0.0289	0.0261
ST_2	0.001	0.004	0.010	0.024	0.048	0.0022	0.0359	0.0169	0.0159
ST_3	0.001	0.005	0.013	0.038	0.078	0.0028	0.0577	0.0274	0.0245
ST_4	0.000	0.002	0.007	0.019	0.039	0.0014	0.0289	0.0137	0.0123
ST_5	0.005	0.017	0.046	0.110	0.210	0.0111	0.1601	0.0745	0.0723
WT_1	0.002	0.006	0.015	0.042	0.085	0.0037	0.0634	0.0299	0.0274
WT_2	0.001	0.005	0.014	0.039	0.080	0.0031	0.0597	0.0283	0.0255
WT_3	0.001	0.004	0.010	0.025	0.049	0.0023	0.0371	0.0174	0.0165
WT_4	0.012463	0.028874	0.044326	0.062679	0.074118	0.0207	0.0684	0.0239	0.0445

Table 7. The output of Gap analysis for IVF- QSPM regarding SO_1 to WO_5

Criteria	SO_1	SO_2	SO_3	SO_4	SO_5	WO_1	WO_2	WO_3	WO_4	WO_5
SO_1	-	-	-	0.346	0.478	-	0.311	-	0.319	-
SO_2	-	-	-	-	0.108	-	-	-	-	-
SO_3	0.887	0.772	-	0.829	0.926	0.442	0.811	-	0.815	0.638
SO_4	-	0.206	-	-	0.234	-	-	-	-	-
SO_5	-	-	-	-	-	-	-	-	-	-
WO_1	0.633	0.662	-	0.684	0.792	-	0.661	-	0.666	0.385
WO_2	-	0.237	-	0.122	0.272	-	-	-	0.088	-
WO_3	0.906	0.780	0.072	0.839	0.935	0.472	0.821	-	0.826	0.656
WO_4	-	0.230	-	0.113	0.264	-	-	-	-	-
WO_5	0.293	0.230	-	0.113	0.264	-	-	-	-	-
WO_6	0.284	0.513	-	0.486	0.608	-	0.455	-	0.462	-
ST_1	0.665	0.677	-	0.703	0.809	0.082	0.680	-	0.685	0.417
ST_2	0.867	0.763	-	0.817	0.915	0.409	0.798	-	0.803	0.617
ST_3	0.697	0.690	-	0.721	0.826	0.134	0.699	-	0.704	0.449
ST_4	0.939	0.794	0.175	0.858	0.953	0.525	0.841	-	0.845	0.689
ST_5	-	0.281	-	0.180	0.326	-	0.139	0.123	0.148	-
WT_1	0.640	0.666	-	0.688	0.796	0.042	0.665	-	0.670	0.392

WT_2	0.678	0.682	-	0.710	0.816	0.103	0.687	-	0.693	0.430
WT_3	0.855	0.757	-	0.810	0.908	0.390	0.791	-	0.796	0.605
WT_4	0.278	0.496	-	0.472	0.594	-	0.442	-	0.449	0.033
GW_j	0.278	0.206	0.072	0.113	0.108	0.042	0.139	0.123	0.088	0.033
NGW_j	0.097	0.072	0.025	0.040	0.038	0.015	0.049	0.043	0.031	0.012
rank	**3**	**5**	12	8	9	18	**6**	**7**	10	19

Continue of table 7 from $WO_6$to WT_4

Criteria	WO_6	ST_1	ST_2	ST_3	ST_4	ST_5	WT_1	WT_2	WT_3	WT_4
SO_1	-	-	-	-	-	0.258	-	-	-	-
SO_2	-	-	-	-	-	-	-	-	-	-
SO_3	0.641	0.407	0.077	0.369	-	0.787	0.436	0.392	0.110	1.257
SO_4	-	-	-	-	-	-	-	-	-	-
SO_5	-	-	-	-	-	-	-	-	-	-
WO_1	0.391	-	-	-	-	0.628	-	-	-	0.731
WO_2	-	-	-	-	-	-	-	-	-	-
WO_3	0.659	0.438	0.131	0.402	-	0.799	0.466	0.424	0.162	1.295
WO_4	-	-	-	-	-	-	-	-	-	-
WO_5	-	-	-	-	-	-	-	-		
WO_6	-	-	-	-	-	0.410	-	-	-	-
ST_1	0.423	-	-	-	-	0.649	0.071	-	-	0.797
ST_2	0.621	0.372	-	0.332	-	0.774	0.402	0.357	0.051	1.215
ST_3	0.454	0.083	-	-	-	0.669	0.123	0.061	-	0.863
ST_4	0.692	0.494	0.228	0.461	-	0.819	0.520	0.481	0.256	1.363
ST_5	-	-	-	-	-	-	-	-	-	-
WT_1	0.398	-	-	-	-	0.633	-	-	-	0.745
WT_2	0.435	0.051	-	-	-	0.657	0.092	-	-	0.823
WT_3	0.609	0.352	-	0.311	-	0.767	0.383	0.336	-	1.190
WT_4	0.043	-	-	-	-	0.397	-	-	-	-
GW_j	0.043	0.051	0.077	0.311	0.000	0.258	0.071	0.061	0.051	0.731
NGW_j	0.015	0.018	0.027	0.109	0.000	0.090	0.025	0.021	0.018	0.256
rank	17	16	11	**2**	20	**4**	13	14	15	**1**

By considering the experimental results of applying Gap analysis for IVF- QSPM given in Table 7, criteria WT_4, ST_3, SO_1, ST_5, SO_2, WO_2, WO_3 (bolded rankings) including more than 70% of the cumulative weights and obtaining the first to seventh ranks in order.

4.2. Ranking the alternatives

Defining the criteria weights as the next stage, we get to the partner evaluation step through which the performance of partners is measured. This evaluation is undertaken by experts who were asked to evaluate and alternatives' score with regards to the selected criteria (strategies) i.e. WT_4, ST_3, SO_1, ST_5, SO_2, WO_2, WO_3. In the case study discussed, following step 3 and according to the experts' opinions, the committee provided a list, including eight eligible applicant partners cooperating as an alliance in SH.KH. To evaluate these eight partners through IVF-MCDMs, the linguistic variables (including numbers 1 to 10) represented in Table 8, based on Vahdani et al. (2012), are applied. The procedure is firstly applied to obtain the experts' opinions on partners based on selected strategies, and secondly, to convert them to the IVF numbers in the case study. The original decision matrix using IVF values of Table

8, is represented in Table 9. Furthermore, the normalized IVF decision matrix is then multiplied to the criteria weights achieved by IVF-QSPM (reported in Table 3) to achieve the weighted normalized decision matrix which is reported in Table 10.

Table 8. Definitions of linguistic variables for rating of alternatives

score	Linguistic variable	Interval-valued fuzzy number
1	Very poor (VP)	[(0,0);0 ;(1,1.5)]
2	Poor(P)	[(0,0.5);1 ;(2.5,3.5)]
3	Moderately poor(MP)	[(0,1.5);3 ;(4.5,5.5)]
4	Fair (F)	[(2.5,3.5);5 ;(6.5,7.5)]
5	Moderately good(MG)	[(4.5,5.5);7 ;(8,9.5)]
6	Good(G)	[(5.5,7.5);9 ;(9.5,10)]
7	Very good (VG)	[(8.5,9.5);10 ;(10,10)]

Table 9. The original fuzzy interval decision matrix of eight alternatives

	SO_1					SO_2				
	a	a'	b	c'	c	a	a'	b	c'	c
A_1	4.5	5.5	7.0	8.0	9.5	2.5	3.5	5	6.5	7.5
A_2	4.5	3.5	5.0	6.5	7.5	8.5	9.5	10	10	10
A_3	4.5	3.5	5.0	6.5	7.5	4.5	5.5	7	8	9.5
A_4	4.5	7.5	9.0	9.5	10.0	4.5	5.5	7	8	9.5
A_5	4.5	9.5	10.0	10.0	10.0	2.5	3.5	5	6.5	7.5
A_6	4.5	9.5	10.0	10.0	10.0	4.5	5.5	7	8	9.5
A_7	4.5	3.5	5.0	6.5	7.5	0.333	0.467	0.667	0.867	1
A_8	4.5	9.5	10.0	10.0	10.0	0.333	0.467	0.667	0.867	1
	WO_2					WO_3				
	a	a'	b	c'	c	a	a'	b	c'	c
A_1	2.5	3.5	5	6.5	7.5	0	1.5	3	4.5	5.5
A_2	4.5	5.5	7	8	9.5	0	1.5	3	4.5	5.5
A_3	0	1.5	3	4.5	5.5	0	0.5	1	2.5	3.5
A_4	4.5	5.5	7	8	9.5	0	0.5	1	2.5	3.5
A_5	2.5	3.5	5	6.5	7.5	0	0.5	1	2.5	3.5
A_6	2.5	3.5	5	6.5	7.5	4.5	5.5	7	8	9.5
A_7	5.5	7.5	9	9.5	10	0	0.5	1	2.5	3.5
A_8	4.5	5.5	7	8	9.5	2.5	3.5	5	6.5	7.5
	ST_3					ST_5				
	a	a'	b	c'	c	a	a'	b	c'	c
A_1	0	1.5	3	4.5	5.5	8.5	9.5	10	10	10
A_2	2.5	3.5	5	6.5	7.5	4.5	5.5	7	8	9.5
A_3	8.5	9.5	10	10	10	0	1.5	3	4.5	5.5
A_4	4.5	5.5	7	8	9.5	2.5	3.5	5	6.5	7.5
A_5	4.5	5.5	7	8	9.5	8.5	9.5	10	10	10
A_6	8.5	9.5	10	10	10	4.5	5.5	7	8	9.5
A_7	0	0.5	1	2.5	3.5	5.5	7.5	9	9.5	10
A_8	8.5	9.5	10	10	10	5.5	7.5	9	9.5	10
	WT_4									

	a	a'	b	c'	c
A_1	0	1.5	3	4.5	5.5
A_2	2.5	3.5	5	6.5	7.5
A_3	4.5	5.5	7	8	9.5
A_4	8.5	9.5	10	10	10
A_5	2.5	3.5	5	6.5	7.5
A_6	2.5	3.5	5	6.5	7.5
A_7	8.5	9.5	10	10	10
A_8	4.5	5.5	7	8	9.5

Table 10. Weighted normalized fuzzy interval decision matrix for eight partners

	SO_1					SO_2				
partners	a	a'	b	c'	c	a	a'	b	c'	c
partner 1	0.004	0.012	0.032	0.069	0.140	0.002	0.009	0.032	0.131	0.291
partner 2	0.005	0.010	0.029	0.071	0.140	0.004	0.018	0.048	0.151	0.291
partner 3	0.005	0.010	0.029	0.071	0.140	0.002	0.011	0.035	0.127	0.291
partner 4	0.004	0.016	0.040	0.078	0.140	0.002	0.011	0.035	0.127	0.291
partner 5	0.004	0.020	0.044	0.082	0.140	0.002	0.009	0.032	0.131	0.291
partner 6	0.004	0.020	0.044	0.082	0.140	0.002	0.011	0.035	0.127	0.291
partner 7	0.005	0.010	0.029	0.071	0.140	0.002	0.009	0.032	0.131	0.291
partner 8	0.004	0.020	0.044	0.082	0.140	0.002	0.009	0.032	0.131	0.291
	WO_2					WO_3				
	a	a'	b	c'	c	a	a'	b	c'	c
partner 1	0.002	0.009	0.033	0.101	0.223	0.000	0.001	0.004	0.017	0.043
partner 2	0.002	0.011	0.037	0.098	0.223	0.000	0.001	0.004	0.017	0.043
partner 3	0.000	0.005	0.027	0.095	0.223	0.000	0.000	0.002	0.015	0.043
partner 4	0.002	0.011	0.037	0.098	0.223	0.000	0.000	0.002	0.015	0.043
partner 5	0.002	0.009	0.033	0.101	0.223	0.000	0.000	0.002	0.015	0.043
partner 6	0.002	0.009	0.033	0.101	0.223	0.000	0.002	0.006	0.018	0.043
partner 7	0.003	0.014	0.045	0.110	0.223	0.000	0.000	0.002	0.015	0.043
partner 8	0.002	0.011	0.037	0.098	0.223	0.000	0.001	0.005	0.018	0.043
	ST_3					ST_5				
	a	a'	b	c'	c	a	a'	b	c'	c
partner 1	0.000	0.001	0.007	0.031	0.078	0.004	0.016	0.046	0.110	0.210
partner 2	0.000	0.002	0.009	0.033	0.078	0.002	0.010	0.034	0.093	0.210
partner 3	0.001	0.005	0.013	0.038	0.078	0.000	0.005	0.025	0.090	0.210
partner 4	0.000	0.003	0.010	0.032	0.078	0.002	0.008	0.031	0.095	0.210
partner 5	0.000	0.003	0.010	0.032	0.078	0.004	0.016	0.046	0.110	0.210
partner 6	0.001	0.005	0.013	0.038	0.078	0.002	0.010	0.034	0.093	0.210
partner 7	0.000	0.001	0.004	0.027	0.078	0.003	0.013	0.041	0.105	0.210
partner 8	0.001	0.005	0.013	0.038	0.078	0.003	0.013	0.041	0.105	0.210
	WT_4									
	a	a'	b	c'	c					
partner 1	0.000	0.008	0.024	0.051	0.074					
partner 2	0.004	0.013	0.030	0.054	0.074					
partner 3	0.006	0.017	0.033	0.053	0.074					
partner 4	0.011	0.027	0.044	0.063	0.074					
partner 5	0.004	0.008	0.030	0.054	0.074					
partner 6	0.004	0.008	0.030	0.054	0.074					

partner 7	0.011	0.016	0.044	0.063	0.074
partner 8	0.006	0.010	0.033	0.053	0.074

The weighted normalized fuzzy interval decision matrix is then applied as the input data for IVF-TOPSIS, IVF-ARAS, IVF-SAW and IVF-COPRAS to investigate the candidate partners.

a. IVF-TOPSIS

Experimental results achieved by IVF-TOPSIS based on cumulative ideal and anti-ideal distances (d_i^-, d_i^+), closeness index (CL_i) and final rank of each alternative is given in Table 11.

Table 11. Closeness index and final rank of each alternative achieved by IVF-TOPSIS

Partner	CL_i					CI_i	Rank
	bottom		medium	top			
	a	a'	b	c'	c		
partner 1	0.3657	0.3176	0.3040	0.5459	0.5056	0.3905	7
partner 2	0.3646	0.3075	0.5945	0.5312	0.5039	0.4827	3
partner 3	0.3658	0.8390	0.4144	0.5987	0.6115	0.5406	1
partner 4	0.3657	0.3199	0.4926	0.4575	0.4459	0.4290	4
partner 5	0.3657	0.3144	0.3368	0.5483	0.5060	0.4013	6
partner 6	0.3657	0.3144	0.2995	0.5479	0.5054	0.3887	8
partner 7	0.3651	0.3133	0.6470	0.5356	0.5047	0.5021	2
partner 8	0.3657	0.3138	0.3969	0.5479	0.5059	0.4212	5

b. IVF-ARAS

The values of optimality function $(\widetilde{S_i})$ as well as the degree of alternative utility (K_i) achieved by IVF-ARAS, are demonstrated in Table 12.

Table12. Experimental results achieved by IVF-ARAS

Partner	S_i^p					$\widetilde{S}_i$	K_i	Rank
	bottom		medium	top				
	a	a'	b	c'	c			
partner 0	0.020	0.080	0.209	0.518	0.995	0.338	-	-
partner 1	0.011	0.049	0.153	0.425	0.880	0.279	0.8232	8
partner 2	0.022	0.077	0.224	0.613	1.260	0.403	1.1920	1
partner 3	0.017	0.059	0.172	0.492	1.044	0.326	0.9636	3
partner 4	0.021	0.073	0.185	0.461	0.949	0.313	0.9234	5
partner 5	0.014	0.058	0.171	0.442	0.880	0.289	0.8554	7
partner 6	0.014	0.059	0.176	0.462	0.958	0.307	0.9079	6
partner 7	0.029	0.077	0.238	0.591	1.164	0.39	1.1510	2
partner 8	0.017	0.065	0.192	0.479	0.961	0.318	0.9391	4

c. IVF-SAW

By implementation of the SAW method, the total score for each algorithm is given in Table 13.

Table13. Experimental results achieved by IVF-SAW

Partner	$\tilde{S}_i$					h_i	Rank
	bottom		medium	top			
	a	a'	b	c'	c		
partner 1	0.0100	0.0490	0.1520	0.4250	0.8800	0.2780	8
partner 2	0.0210	0.0760	0.2250	0.6130	1.2600	0.4033	1
partner 3	0.0160	0.0580	0.1710	0.4930	1.0450	0.3257	3
partner 4	0.0200	0.0720	0.1860	0.4620	0.9490	0.3125	5
partner 5	0.0130	0.0590	0.1710	0.4410	0.8800	0.2892	7
partner 6	0.0130	0.0590	0.1760	0.4620	0.9580	0.3073	6
partner 7	0.0290	0.0770	0.2380	0.5920	1.1630	0.3895	2
partner 8	0.0170	0.0650	0.1920	0.4800	0.9600	0.3177	4

d. IVF-COPRAS

For the IVF-COPRAS method, the results including the sum of the beneficial criteria values$\widetilde{p_\iota}$, the relative weight of each alternative ($\widetilde{Q_\iota}$), and the utility degree of each alternative (N_i) is obtained according to Table 14.

Table14. Experimental results achieved by IVF-COPRAS

Partner	$\tilde{p}_i$					$\widetilde{Q_\iota}$	N_i	Rank
	bottom		medium	top				
	a	a'	b	c'	c			
partner 1	0.011	0.049	0.153	0.425	0.880	0.279	72.042	8
partner 2	0.017	0.068	0.209	0.589	1.229	0.387	100.000	1
partner 3	0.014	0.051	0.161	0.480	1.024	0.315	81.442	4
partner 4	0.018	0.067	0.183	0.466	0.969	0.314	81.222	5
partner 5	0.022	0.080	0.193	0.464	0.899	0.309	79.791	6
partner 6	0.015	0.059	0.176	0.462	0.958	0.307	79.485	7
partner 7	0.018	0.061	0.202	0.549	1.120	0.358	92.695	2
partner 8	0.026	0.077	0.221	0.513	0.989	0.341	88.191	3

The ranking results of applied MCDM methods have been presented in Table 15.

Table 15. The ranking results of MCDM methods applied

Partner	IVF-TOPSIS	IVF-ARAS	IVF-SAW	IVF-COPRAS
partner 1	7	8	8	8
partner 2	3	1	1	1
partner 3	1	3	3	4
partner 4	4	5	5	5
partner 5	6	7	7	6
partner 6	8	6	6	7
partner 7	2	2	2	2
partner 8	5	4	4	3

5. Discussion

5.1. Aggregation of results achieved through the utility interval method

According to Table 11, the application of different MCDMs methods for the partner selection case study has led to different ranking orders of alternatives and thus different results. Therefore, an accurate aggregation method is required to provide the final evaluation of the partners and to assist managers in selecting the best partners. With respect to a shortcoming of the usual combination methods (like averaging function, Borda, Copeland rules, etc.), in this paper we aggregate the outcomes of the MCDM methods implemented, based on the utility aggregation method proposed by Wang et al. (2005). We prefer this over other aggregation methods as it is a simple linear programming (LP) based method with high accuracy and wide application in various fields to generate an aggregated ranking in group decision situations. Besides, this method can provide information on the degree of preference, which enables comparison of the results on different levels.

In the utility interval aggregation method, initial LP models are constructed and solved to estimate the interval for each ranking method (see Eqs. (40) to (43)).

$$\min / \max u_{i1} \tag{40}$$

$$u_{ij} - u_{i\,j+1} \geq \varepsilon_{j\,j+1} \quad j = 1, 2, \dots, n-1 \tag{41}$$

$$\sum_{j=1}^{n} u_{ij} = 1 \tag{42}$$

$$u_{ij} \geq 0 \quad j = 1,2, \dots, n \tag{43}$$

Where u_{ij} is the utility of the j^{th} ranked alternative proposed by the i^{th} MCDM method.

The objective function finds the lower bound and upper bound of intervals determined by each MCDM method, for the first ranked alternative. Eq. (31) determines the priority of the j^{th} partner to the next ranked partner in the i^{th} MCDM method. Epsilon (ε) is considered as a small positive number calculated through Eq. (44), in which n denotes the number of candidate partners (n=8) (Wang et al., 2005). Therefore, for the pilot study, ε will be a positive number in the range 0 and 0.035 (the range of 0 to 0.035 is divided into three equal ranges). Three sets of evaluations are run for ε 0, 0.017 and 0.035. Higher sets of evaluations like: 0, 0.0085, 0.025 and .0.035 and even bigger sets were also checked, however no new aggregated ranking was achieved. Therefore, the authors set the number of epsilon runs as three.

$$0 \leq \varepsilon \leq \frac{1}{\frac{n(n-1)}{2}} \tag{44}$$

The output of this step is the utility estimated intervals associated with the MCDM methods.

Then, the relative weight of each ranking method is calculated regarding the weighted average utility or the aggregated utility interval for each alternative. In the primary version of the methodology by Wang et al. (2005), this is calculated by a correlation matrix between MCDMs; however, in this research the relative weights of ranking methods are computed through the entropy method (Shannon and Weaver, 1998). The main advantage of the entropy method over conventional methods is that it is very useful in cases where decision-makers conflict on the values of weights, and where the weights are pretty close to each other (Singh, 2011). The normalized decision matrix as the input data of the entropy method and criteria weights based on Shannon and Weaver (1998), are depicted in Table 16.

Table 16. Input data and final weight of the entropy method

Partner	IVF-TOPSIS	IVF-ARAS	IVF-SAW	IVF-COPRAS
partner 1	0.1098	0.1061	0.1223	0.1067
partner 2	0.1357	0.1537	0.1249	0.1482
partner 3	0.1520	0.1243	0.1191	0.1207
partner 4	0.1206	0.1190	0.1264	0.1204
partner 5	0.1128	0.1103	0.1267	0.1182
partner 6	0.1093	0.1171	0.1257	0.1178
partner 7	0.1412	0.1484	0.1270	0.1374
partner 8	0.1184	0.1211	0.1279	0.1307
Entropy weight	*0.3519*	*0.4005*	*0.0121*	*0.2354*

Finally, the weighted average utility intervals corresponding to three sets of evaluations ε= 0, 0.017, and 0.035 as well as the aggregated rankings, are given in Tables 17 and 18.

Table 17. The weighted average utility interval for ε= 0, 0.017 and 0.035

ε	partner 1	partner 2	partner 3	partner 4	partner 5	partner 6	partner 7	partner 8
0	[0,0.1144]	[0.0809,0.7253]	[0.0294,0.4311]	[0, 0.1882]	[0, 0.1372]	[0, 0.1316]	[0, 0.441]	[0, 0.2283]
0.017	[0.0042,0.061]	[0.1421,0.465]	[0.0974,0.2989]	[0.0513,0.1457]	[0.0241,0.0929]	[0.0189,0.0849]	[0.0942,0.3154]	[0.0628,0.1773]
0.035	[0.0082,0.0108]	[0.2009,0.2156]	[0.1628,0.1719]	[0.1005,0.1048]	[0.0472,0.0503]	[0.037, 0.04]	[0.1847,0.1947]	[0.123, 0.1283]

Table 18. The aggregated rankings achieved by the utility interval aggregation method

Aggregated rankings								
ε	partner 1	partner 2	partner 3	partner 4	partner 5	partner 6	partner 7	partner 8
0	7	1	2	5	6	8	3	4
0.017	7	1	3	5	6	8	2	4
0.035	8	1	3	5	5	7	1	4

The graphical comparison between the applied MCDM methods and the aggregation method is displayed in Figure 2.

It is clear that under all assumptions of ε, partner 2 is superior to other partners but the ranking between the second and third best alternatives changes between partner 3 and partner 7, and even when ε takes the maximum value ($\varepsilon = 0.035$), partner 7 obtains the highest ranking. It is inferred that under the assumption of weak orders ($\varepsilon = 0$ *and* 0.017), partner 2 is significantly superior to others, but under the strict order ($\varepsilon = 0.035$), partner 7 is also superior.

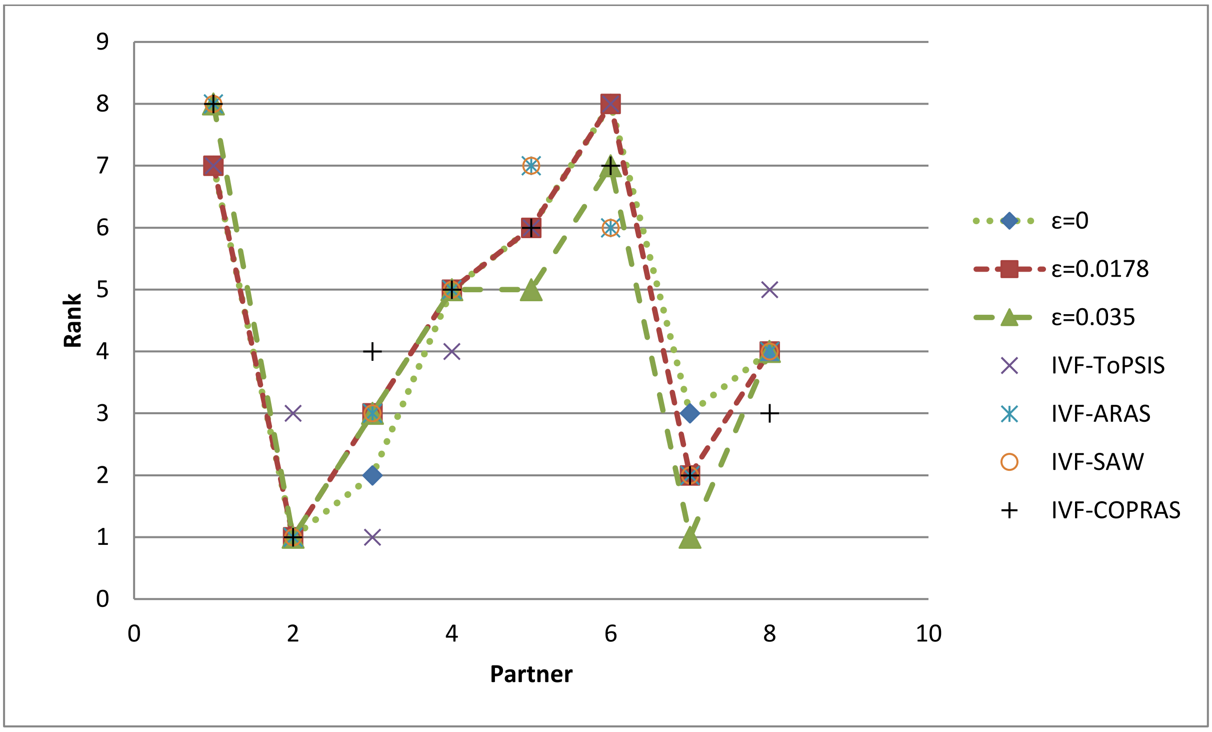


Figure 2. Graphical comparison between utility aggregation ranking and MCDMs

5.2. Sensitivity Analysis

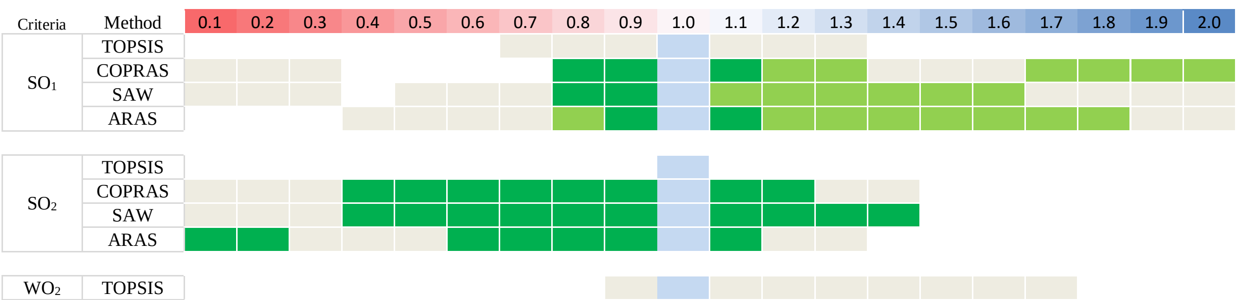
Ranking results achieved by MCDM methods are inherently affected by the nature of criteria as well as the distribution of weighting among criteria (Maliene et al., 2018). Therefore, in this section, firstly we aim to evaluate the impact of the change of criteria weight on ranking results achieved by each method, and secondly to find out how robust the implemented MCDM methods are. To do this, Figure 3 reflects the variation of criteria weights and the monitoring of changes that occur in the final ranking of alternatives achieved by the proposed MCDM methods. It should be noted that the dark green parts of Figure 3 demonstrate no sensitivity of alternatives' ranking to the changes that occurred in criteria weight, whilst the light green parts indicate the single change in ranking. Afterwards, the grey and white panels respectively, contribute to two changes, and more than two changes made to the ranking. The criteria and proposed MCDM methods are displayed at the left side of the panel where the horizontal axis stands for the variation of criteria weight ranging from 0.1 to 2. It is worth mentioning that any changes in criteria weights were reported while other criteria remained unchanged. Obviously, as for WO_3, all four proposed MCDM methods show the least sensitivity, according to which WO_3 is specified as the most robust criteria. On the other hand, WT_4 is noted as the most critical criteria among them all. Considering WT_4, more than two changes in the existing ranking of the alternatives were distinguished in most of the parts. Furthermore, the sensitivity coefficient (SC_{ij}) has been calculated for the i^{th} method, considering the j^{th} criterion. According to Eq. (45), SC_{ij} calculates the average value of changes in alternative ranking results by each method, when the criterion weight alters.

$$SC_{ij} = \frac{\sum_{w=1}^{W} D_{ij}^{w}}{F} \qquad \forall\, i, j\,, w \in \{0.1, 0.2, 0.3, \dots, 0.9, 1.1, 1.2, \dots, 2\} \tag{45}$$

Where SC_{ij} denotes the sensitivity coefficient of method *i* to criterion *j*, D_{ij}^{w} corresponds to the number of changes that occurred in the alternative ranking result by method *i*, when the weight of criterion *j* varies in the defined range. Besides, *F* stands for the frequency of changes in the criteria weights. Note that the criteria weight alters in the range of 0.1 to 2 with 0.1 steps (including 19 total steps). As can be seen from Figure 4, the variation of criteria weight in IVF-TOPSIS leads to a higher change in the ranking results. Eventually, the total average of changes in the alternative rankings relating to each method namely SC_i^*, being calculated through Eq. (46), has been computed to detect the most robust method.

$$SC_i^* = \frac{\sum_{j=1}^{J} SC_{ij}}{J} \qquad \forall\, i, j \tag{46}$$

where J stands for the number of criteria. Figure 5 depicts SC_i^* for the proposed IVF-TOPSIS, IVF-COPRAS, IVF-SAW and IVF-ARAS. It is obvious that IVF-SAW and IVF-COPRAS reflect the first and second robust methods in order, whereas IVF-TOPSIS is noted as the least robust method.



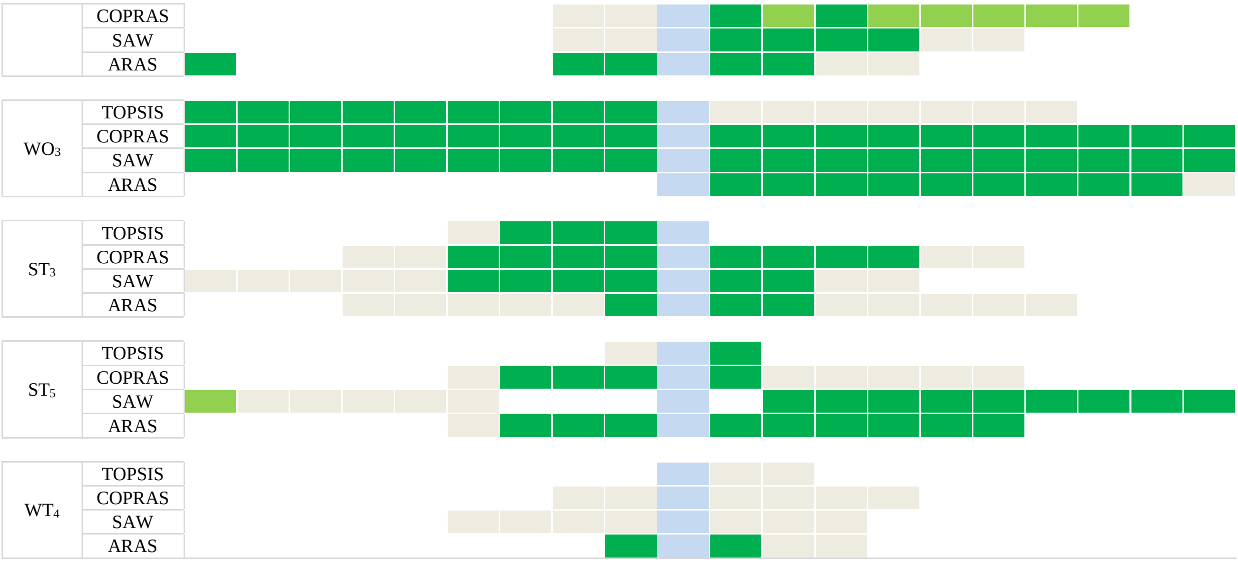


Figure 3. Criteria sensitivity to the change

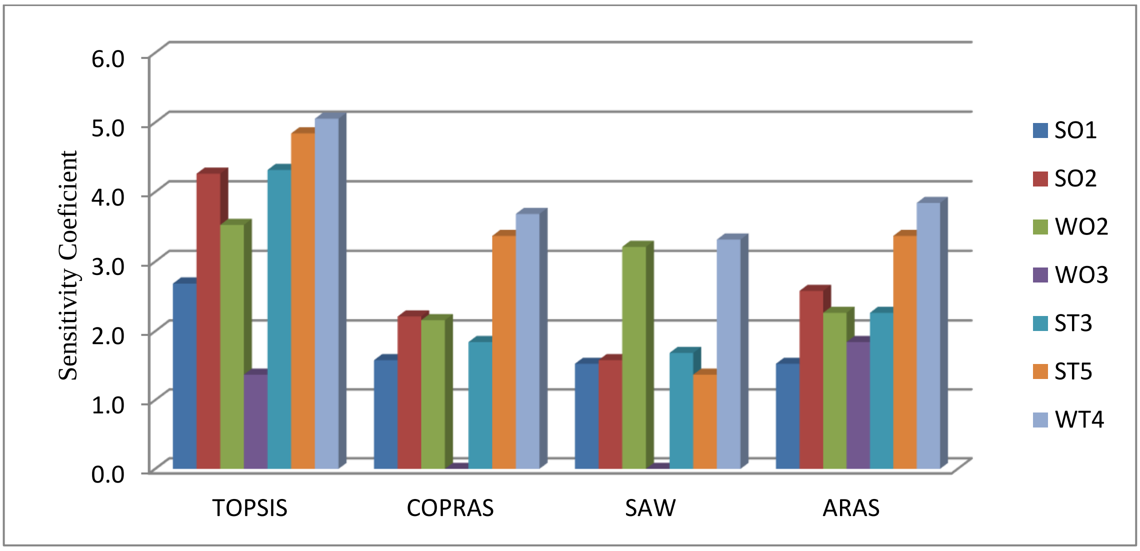


Figure 4. Sensitivity coefficient (SC_{ij})

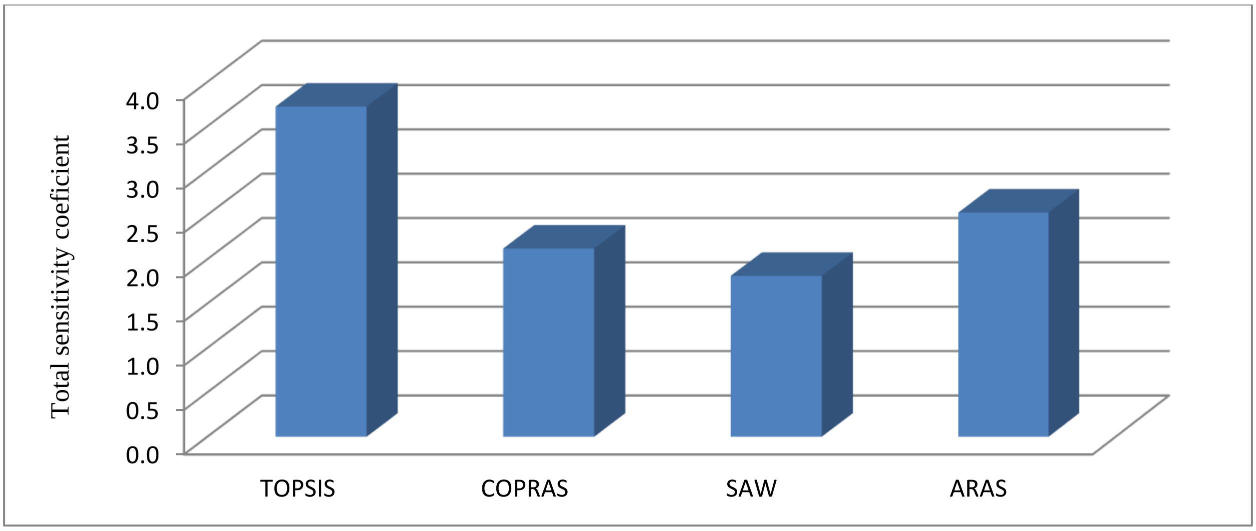


Figure 5. Total sensitivity coefficient ($\boldsymbol{SC_i^*}$)

5.3. The managerial and technical implication

This research represents an integrated methodology for general strategy rankings and selection problems to efficiently reduce the vagueness of the whole decision-making process. This includes defining the affecting criteria, weighing the affecting criteria, determining the best alternatives with an integrated model, and evaluating the robustness of results achieved. It is notable that the proposed methodology is relevant enough to practitioners and managers to be applied in various fields of decision-making and is not restricted to strategic alliance selection. The reasons for this claim are highlighted below:

1. The output of the QSPM with Gap analysis could be generally applied to find the most significant criteria in every high-level managerial decision-making problem, which has been encountered (with contradicting solutions). By omitting fewer affecting criteria and measuring the criteria weight, the integrated model makes the decision-making process more straightforward and transparent and guarantees the validity of results. The proposed QSPM-Gap methodology helps the managers in strategy reduction by focusing clearly and avoiding any misleading because of a large number of potential solutions and strategies.
2. Due to the uncertain nature of real-world decision-making problems that originate from the complexity of real data, the specification of criteria weights for managers and decision makers is strictly impossible. In this case, the application of IVF data sets to describe and treat imprecise and uncertain factors of decision-making problems introduces more accuracy and authenticity to the decision-making support system.

3. The sensitivity analysis evaluates the impact of the change of criteria weight on ranking results and the robustness of the proposed methodology which increases the trustworthiness of the model. Therefore, the proposed interval fuzzy methodology is robust enough to be applied in any managerial implication.

4. One of the main concerns in using MCDM algorithms at a managerial level is justifying the reason for using a specific MCDM model or a group of models for the ranking purpose. This paper, with the combination of the MCDM models via a utility interval-based approach considers the MCDM combination at different levels which enhances the decision options for the managers. Moreover, the selected models have the lowest correlation, therefore the results have to be more general and reliable.

6. Conclusion

The partner selection problem aims to investigate a list of potential partners in order to choose the one with the best skills, knowledge, capabilities and competencies. These criteria improve the flexibility of organizations to gain lower completion times and higher qualities of products and services.

This research aims to answer two main questions of outsourcing and the partner selection problem: how to manage the strategic decisions within the outsourcing process, and how to outsource or select the partners. To attain these goals, an innovative framework has been developed for the first time using a combination of SWOT- IVF QSPM with Gap analysis to define the significant outsourcing strategies and weighing the resulted strategic features.

Moreover, regarding the inevitable uncertainty and complexity of outsourcing data, the implication of the IVF version of all methods is taken into consideration. This fact could enhance the ability of the algorithms to deal with the uncertainty and vagueness of outsourcing challenges in describing the importance of affecting criteria and introducing more accuracy in the ranking of alternatives.

Using a single MCDM method for prioritization, the partners cannot ensure the best result, and thus four different IVF-MCDM algorithms are implemented to find the best partner. The application of various MCDM methods may yield different results. Therefore, the aggregation of the results causes a robust selection of the appropriate partner. Concerning a shortcoming of usual combination methods (like averaging function, Borda, Copeland rules, etc.), we implemented the utility interval technique because of its capabilities in considering different degrees of preference.

The main limitation of this research might be regarded as the inherent inconstancy of MCDM techniques for ranking the alternatives. In real world problems, different MCDMs offer diverse solutions with no significant convergence. This fact actually underlines the idea of implementing aggregation methods.

The other limitation is associated with not considering all the effective criteria in the problem. Although we followed the Gap analysis and the Pareto analysis to take the most effective criteria into account, investigating all the existing criteria might introduce new and better ranking of alternatives while increasing the complexities of the problem and hardening the experimental computing.

For future studies, the research offers the application of new types of fuzzy numbers like hesitant or grey fuzzy sets to extend the model flexibilities. Focusing on other MCDM algorithms to compare the results with the results of this research could be seen as another further study opportunity. Another potential for the further development of the problem is the application of the green and sustainable strategic partner selection by observation of both social and environmental aspects of partner selection. Besides, consideration of the negative criteria in the list of acquired criteria under which the alliance and partnership could be broken down can improve the quality of decision-making in the utilization of the rational alliances and maximizes the potential ability of MCDM algorithms.

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