Strategic supplier selection: a fuzzy multicriteria approach

Selección de proveedores estratégicos: un enfoque multicriterio difuso

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Abstract
Selecting suppliers has become a strategic problem for firms interested in the establishment of long-term partnerships. This strategic decision is related to the suppliers' capabilities to effectively collaborate with the customer. This study identifies three organizational capabilities that enable partnership and proposes a multicriteria group decision making methodology for supplier selection based on widely used methods that are easy to implement and enhance the objectivity of the strategic selection of suppliers Specifically, the methods Fuzzy LinPreRa and extent Fuzzy Analytical Hierarchical Process (FAHP) are compared. They were applied to an empirical case and the results indicated LinPreRa is as appropriate as extent FAHP but easier to apply.
key words: strategic supplier selection; multi-criteria group decision making; organizational capabilities; FAHP; LinPreRa

Resumen
La selección de proveedores se ha convertido en un problema estratégico para empresas interesadas en el establecimiento de asociaciones a largo plazo. Esta decisión estratégica está relacionada a las capacidades de los proveedores para colaborar efectivamente con el cliente. Este estudio identifica tres capacidades organizacionales que facilitan la asociación y propone una metodología de decisión multicriterio grupal para la selección de proveedores basándose en métodos ampliamente usados y que son fáciles de implementar y que mejoran la objetividad de la selección estratégica de proveedores. Específicamente, el método LinPreRa difuso y el método de extensión para el Proceso Analítico Jerárquico Difuso (FAHP) fueron comparados y mediante un caso empírico mostramos que LinPreRa difuso es un método apropiado y más fácil de utilizar que el método de extensión FAHP.
Palabras claves: selección de proveedores estratégicos; toma de decisiones multicriterio grupales; capacidades organizacionales; FAHP; LinPreRa

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1. Introduction

The extant literature argues value creation involves collaborative practices with suppliers where traditional roles are intertwined and buyers and suppliers need to develop new capabilities (Möller, 2006). Some collaborative projects with critical suppliers demonstrate that strong relational and strategic capabilities are the basis for the development of new products (co-design) and the improvement of process and products (Sammut-Bonnici, 2015). For example, the collaboration between Corning and Sharp has enabled the manufacturing of a larger and environmentally friendly LCDs while Honda shares with its suppliers what products intends to develop as well as what improvements are necessary to enhance the quality and costs of current products. In some industrial sectors such as the automotive, over 50% of the total product components are manufactured by external suppliers. Consequently, their performance affects the cost and quality of the complete product while inappropriate buyer-supplier relations may even have a negative influence on the supply chain process (Chan & Kumar, 2007).

However, the establishment of strategic partnerships with suppliers may be difficult because it requires of skills, routines, cooperation and a common culture, thus a reliable process of partner selection is crucial (Masteika & Čepinskis, 2015). Traditionally, supplier selection has been based on operational and tangible criteria associated with efficiency goals, such as price, product quality and delivery time (Chai & Ngai, 2015). But recently, more abstract criteria such as problem-solving capacity, customer orientation, reliability and innovation have been considered (Lu, Goh, & De Souza, 2016). These criteria are focused not just on assuring a proper supplier's performance but on value co-creation between buyers and suppliers (Möller, 2006). Goal settings have been suggested as the basis to define the configuration –continuity, complexity, intensity and symmetry- of the relation with suppliers (Roseira & Brito, 2014). These goals may range from operational efficiency to increasing the competitiveness of the buyer-supplier dyad through resource integration and innovation (Arroyo-López, Holmen, & De Boer, 2012; Revilla & Knoppen, 2015). The objective of this study is to evaluate potential suppliers based on the organizational capabilities that are a pre-condition for knowledge integration provided the firm's ability to manage the buyer-supplier relationship and make the adequate investments to enable value co-creation (Verweij & Peek, 2013; Roseira & Brito, 2014).

Because organizational capabilities are abstract and multi-dimensional concepts, the use of such constructs as criteria for supplier selection implies ambiguous judgments regarding its importance. Therefore, fuzzy multicriteria methods become relevant to take care of the imprecision in the judgments of decision makers (Ho, Xu, & Dey, 2010). Accordingly, the literature review section comprises two parts: first we define the concept of organizational capability and identify those that are critical for collaborative partnerships. In the second part, we discuss multicriteria decision-making methods (MMDM) making emphasis on fuzzy MMDM. The third section of this article describes the methodology proposed in this work to select suppliers with the strategic goal of establishing partnerships that may yield strategic advantages for the buyer-supplier dyad. In the fourth section, the proposed methodology is applied to a case study regarding the selection of strategic suppliers of the automotive sector. Two fuzzy MMDM methods are applied, fuzzy LinPreRa and extent fuzzy AHP, to determine the weights of the criteria according to the experience of four decision makers. The results and discussion section compare the two methods on the basis of their practicality in an industrial context. Finally, the last section states conclusions along with academic and practical implications.

2. Literature review

2.1. Organizational capabilities as enablers of supplier-buyer partnerships

An organizational capability refers to the capacity of the firm to perform a particular activity in a reliable and at least minimally satisfactory manner (Helfat et al., 2009). The concept implies a practiced or patterned behavior because a capability enables the reliable repetition of an activity, otherwise it cannot be considered a capacity. Moreover, the required minimally satisfactory performance implies the output of the activity achieves an established standard, if not, one cannot say the organization has the capability. From a strategic perspective, capabilities define firms' heterogeneity and because they are more difficult to copy than technology or market capital, they represent a potential source of competitive advantage.

Previous research has classified capabilities in different levels. A basic categorization is between operational and dynamic capabilities (Helfat et al., 2009). Operational or ordinary capabilities are those that enable a firm to perform an activity using the same techniques, for example to manufacture the same automotive part. In contrast, dynamic capabilities enable a firm to alter the current status, modify/improve operational capabilities or adapt to sudden or discontinuous changes in its business environment (Teece, 2007). Examples of dynamic capabilities include innovation in products and creation of strategic alliances to enhance the resources of the firm.

Because of the dynamism of the business environment, a precise threshold of change that separates operational from dynamic capabilities cannot be defined. Therefore, Helfat and Winter (2011) recognize there are integrative capabilities that enable intra- and inter-firm communication and coordination. These capabilities can serve an operational purpose or support adaptation and drive innovation. For example, transmitting information about product flows corresponds to an operational activity but the increased visibility may improve the efficiency of the supply chain through process integration.

The development and maintenance of capabilities entails the acquisition and use of resources. Therefore, it is critical to assess what capabilities are required depending on the firm's context (e.g. a financial services firm must have risk management capabilities) and the nature and speed of change that a capability enables (e.g. the innovation capability of a high-tech firm). The ability to perform an activity requires a bundle of interdependent capabilities. For example, in the case of product co-design, inter-firm collaboration and performance accountability are direct capabilities identified, but the ability to learn and a shared strategic view are also relevant (Ulrich & Smallwood, 2004).

By using a capability-building and knowledge-based view perspective, Revilla and Knoppen (2015) argue knowledge integration is a unique capability that allows the evolution and enhancement of the knowledge base of the buyer-supplier dyad through the execution of joint projects. Knowledge per se may not provide value, but if properly processed and utilized in bundles, that is if integrated with existing technical capabilities, results in operational efficiency, innovation and even competitive advantage because it is dyad-specific and resides in processes rather than in resources. Consequently, it is important for companies to decide with what partners share and create new knowledge to improve existing products and innovate.

The relational strategic view recognizes relational capabilities enable firms to acquire valuable (external) resources and combine them with their own resources to gain and sustain competitive advantage. The "development of relational competencies requires that firms adopt a collaborative managerial mindset for building strategic advantage" (Paulraj, Lado, & Chen, 2008). Based on a relationship marketing approach,

Spekman and Carraway (2006) assert that the transition to collaborative relationships requires of certain capabilities that facilitate the process of partnership, drivers that push the relationship and enablers that help firms to overcome unexpected problems and sustain their collaborative efforts. These three categories of elements prevent from opportunism, tie partners and help to outline the rules for cooperation.

In the case of buyer-supplier partnerships, collaboration is described as an inter-organizational ability that allows participants to agree about goals and responsibilities, share information and invest resources to solve joint problems (Soosay, Hyland, & Ferrer, 2008). Thus, we propose collaboration is a key relational capability that facilitates partnership. Because joint projects imply high appropriability risks and knowledge sharing, trust is key to prevent opportunism and ensure the attainment of mutual goals (Spekman & Carraway, 2006). Lack of trust refrains cooperation with supply chain partners (Revilla & Knoppen, 2015). Additionally, research suggests commitment is critical for resource investment in the relationship, the establishment of norms and the mutual interpretation of specialized knowledge (Lettice, Wyatt, & Evans, 2010). Finally, inter-organizational communication has been recognized as a relational competence that supports strategic collaboration (Paulraj et al., 2008). Open and continuous communication helps to align objectives, share tacit knowledge, develop a common vocabulary and resolve potential conflicts to advance a project (Martins, 2016). Therefore, in this work, the capability for collaboration is considered a multi-dimensional construct comprising three facilitating capabilities or key enablers. They are: trust, commitment and communication.

Joint-decision making is defined as the "application of collaboratively acquired knowledge to jointly make decisions related to interlinked operative processes" (Revilla & Knoppen, 2015). Joint decision making (JDM) provides the experience required to understand how to coordinate shared processes such as sourcing, production planning and product development. When working together, JDM allows negotiation and fine-tune solutions. As a result, activities are more efficiently performed resulting in increased productivity, reciprocity, lower costs and the advancement of knowledge integration (Revilla & Villena, 2012). Therefore, joint-decision making is considered another critical capability that facilitates the use of the supplier's capabilities at different technical interfaces. The extent to which joint decisions regarding operational activities such as sourcing, as well as strategic decisions such as what products to develop, was asked to evaluate this capability. Furthermore, the extent to which JDM is perceived as a win-to-win practice in which none of the parties exerts power to force coordination and value is created for buyer and supplier is considered as another dimension of this capability y (Lettice et al., 2010).

Finally, there is the absorptive capacity of the supplier. This is the set of capabilities a firm has to recognize, assimilate, transform and exploit the external knowledge to transform and produce an organizational capability (Cohen & Levinthal, 2000). Absorptive capability is associated with the ability to learn of the organization and because knowledge is a strategic asset, absorptive capacity is recognized amongst the most influential factors of innovation and organizational performance. Because collaborative projects initially involve the transfer of new knowledge from the buyer to the supplier, the ability to process, interpret and transform this external knowledge is critical to collaborate with the customer and to enable value co-creation (Martins, 2016). To evaluate absorptive capacity, the multi-scale developed and validated by Arroyo et al. (2012) in the context of supplier development was used. The scale comprises three dimensions related to three sequential processes: recognition and acquisition of technical knowledge relevant to joint projects; knowledge integration, i.e. the assimilation and internalization of the external knowledge, and finally, its utilization for innovation and the improvement of products and processes.

2.2. Multicriteria decision-making methods for supplier selection

Multicriteria decision (MCD) problems involve the selection of the "best" alternative from a set of options, based on more than one attribute or criteria (Hwang & Masud, 2012). Because several criteria need to be evaluated simultaneously and some of them may be in conflict, MCD problems are difficult. To clarify this, suppose s suppliers are going to be evaluated based on n criteria, and the objective is to select the best one. It will be infrequent that a unique supplier surpasses all others on all criteria, therefore decision makers (DMs) may proceed by specifying only a few key selection criteria (e.g. price and product quality) or identify which supplier(s) has satisfactory levels on most of the criteria. Degrees of importance or weights may also be assigned to each criterion to compute an aggregated score to evaluate suppliers.

Given the relevance of deciding with which suppliers to establish collaborative relationships, the selection procedure must be fair, reliable and represent low risk and maximum value for the buyer. Therefore, it is necessary to use systematic and consistent methods for supplier selection that take into consideration all the criteria relevant to the organization's goals, which are easy to implement and understand. Criteria for evaluation may be tangible, as is the case of delivery time which is a quantitative and precisely measured criterion. But there are also intangible criteria such as the organizational capabilities of the potential partner; these criteria are highly abstract concepts that involve measurement imprecision. Furthermore, the selection of suppliers is usually a group decision-making problem, where managers of different areas participate. The perspective and specific objectives of each area manager regarding the relevance of the criteria may affect the decision, therefore, these preferences must be "balanced" to get a final decision. Thus, supplier selection is acknowledged as a multicriteria group decision-making (MCGDM) problem (de Araújo & Alencar, 2015).

Several MCDM analysis methods have been used for supplier selection; the underlying idea of the most popular methods is to aggregate all criteria into a single function. Ayhan (2013) groups these methods into three broad categories: a) Value measurement models, based on the assignment of degrees of importance to criteria such as the Analytical Hierarchical Process (AHP) and multi-attribute utility models; b) Goal or reference models that contrast alternatives against an ideal, among them Goal Programming and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and c) Outranking methods such as Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) and ELimination and Choice Expressing REality (ELECTRE) that use a non-compensatory logic to aggregate the criteria and construct an outranking relation on the set of alternatives. This kind of methods consider the relative importance of each criterion but also the extent a criterion must surpass another to be preferred. To do this, veto (ELECTRE), indifference and preference thresholds (PROMETHEE) are established according to the DMs' requirements.

Several of the previous methods may use qualitative or quantitative criteria and have been extensively used because of their flexibility and simplicity (Deng, Hu, Deng, & Mahadevan, 2014). Particularly, AHP and its variants, the Analytical Network Process (ANP) which solves MCD problems with interrelated and qualitative criteria, and FAHP that handles the ambiguity in the judgment of the criteria relevance have been applied in a large variety of MCD problems (Hallikainen, Kivijärvi, & Tuominen, 2009). AHP is based on a concept of balance used to determine the overall importance of the criteria defined for a specific problem. Normalized weights are obtained by structuring the multiple criteria on hierarchical levels and assigning a relative importance for each level of criteria with respect to the upper level. This process is accomplished by asking DMs to make pairwise comparisons between criteria and then aggregate the individual ratings of importance (Deng et al., 2014). Still, AHP is not able to mimic the uncertainty and inaccuracy of judging how preferable or relevant is one criterion over another.

The use of linguistic labels to assess the relative importance of criteria has been used to capture the vagueness in DMs preferences. Calculation procedures are based on the principles of fuzzy set theory since the judgments are no longer described by hard numbers. For example, Dong and Cooper (2016) combine TOPSIS with Linear Programming Technique for Multidimensional Analysis of Preference (LINMAP) to develop a hybrid MCGDM that uses trapezoidal fuzzy numbers to derive a collective and distinctive ranking of alternatives in a fast, effective and flexible manner. In addition to the introduction of fuzziness to the foremost methods and the development of hybrids, other approaches, for example the best-worst method (Safarzadeh, Khansefid, & Rasti-Barzoki, 2018) and artificial intelligence-based models such as Artificial Neural Networks (ANN) have been applied to improve precision and process more information at high speed when solving MCGDM problems (Asthana & Gupta, 2015).
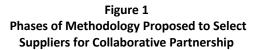
The use of fuzzy numbers in the AHP fundamental scale better shapes the inherent imprecision of the DM's linguistic valuation when making pairwise comparison of criteria of the same hierarchical level. The applicability of this method has been demonstrated for example by Ayhan (2013) to select suppliers with respect to five criteria. However, in despite of its wide use, FAHP methodology has some drawbacks. Among them, the total number of paired comparisons decision makers need to perform and the consistency of these comparisons. Getting consistent or near consistent comparisons matrices may require many reconsiderations by decision makers, and the priorities are dependent on the method used to derive them (Ishizaka, 2012). Expecting that decision makers achieve only consistent comparisons is unrealistic and laborious, thus other methods that overcome these difficulties have been proposed (Wang & Chen, 2008).
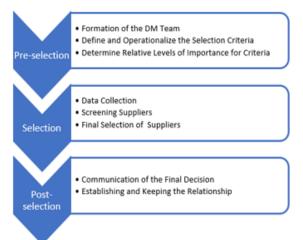
In spite of the large variety of methods available in the MCDM literature, actual applications frequently use simple and easy to understand methods that can be easily implemented without the assistance of experts and advanced technical tools (Durán & Aguiló, 2006; Osorio, Garcia, & Manotas, 2018). Looking to satisfy this practical issue, in this work we compare fuzzy analytic hierarchy process (FAHP) with fuzzy LinPreRa to determine the appropriateness of these methods in the case of comparing criteria with a high level of complexity such as the organizational capabilities of strategic suppliers.

Thus, this study adds to the literature on supplier selection in three ways. First, by proposing organizational capabilities as novel criteria for selection of suppliers. Three capabilities, recognized as enablers of partnership are identified: collaboration capability, joint decision-making capability and absorptive capabilities. Second, we empirically show that fuzzy LinPreRa is an appropriate and simple methodology to compute the weights of selection criteria. And finally, we propose the use of a clustering algorithm to reduce the number of suppliers to be fully evaluated before making a final selection of a strategic partner. Filtering suppliers represents an advantage when the evaluation criteria are difficult to assess as is the case of organizational capabilities.

3. Methodology

Three stages of the supplier selection process have been acknowledged (Punniyamoorthy, Mathiyalagan, & Parthiban, 2011): 1) Pre Selection stage where management sets the goals to be attained through the process; 2) Selection stage that includes all the selection procedures, starting with many potential suppliers and ending with the most suitable candidates; and 3) Post Selection stage that deals with the establishment of the relationship with selected supplier(s). The stages of the process are detailed in Figure 1.

Figure 1
Phases of Methodology Proposed to Select
Suppliers for Collaborative Partnership

1. Pre-selection. The first activity of this stage is the integration of a decision-making team (DMT) which includes *m* DMs from different functional areas responsible or related to the supplier selection process (e.g. R&D, manufacturing, supplier management, etc.). The number and definition of criteria is performed by the DMT based on the goals of the organization (strategic versus operational) and the configuration of the buyer-supplier relationship (Chou & Chang, 2008). The second activity, operationalization of criteria, requires the creation of a hierarchy describing the specific and measurable indicators (qualitative or quantitative) to be used to infer the abstract or latent criteria. The final activity of this stage is the computation of a group vector of weights using as inputs the individual pairwise comparisons performed by each DM. The use of the linguistic scale shown in table 1 allows taking into account the vagueness of the DM's judgments.

Table 1
Fuzzy Evaluation Scale

Linguistic Terms	Fuzzy Number		
	Lower(l)	Medium(m)	Upper(u)
Equal	1	1	1
Weak	1	3	5
Fairly Strong	3	5	7
Very Strong	5	7	9
Absolute	7	9	11

The Fuzzy LinPreRa method and the FAHP method are applied in this work to integrate the evaluation of all DMs in a unique group-vector of weights $\overrightarrow{GWOC}$. These two MCDM approaches are proposed because they are well-grounded and take into account the fuzziness of the DM's judgments. In the case of FAHP we use the method outlined by Chang (1996) to calculate the fuzzy synthetic extent of the DM's judgements. The other methodology, LinPreRa, proposed by Wang and Chen (2008) as alternative to FAHP has two advantages: it requires a smaller number of pairwise comparisons and prevents the inconsistency of the decision matrices (Herrera-Viedma, Herrera, Chiclana, & Luque, 2004). Individual judgments are aggregated to get a group decision matrix GA. The

simplest way to construct this matrix is to average the preferences of each decision maker on each criterion and sub-criterion provided the variability of individual pairwise comparisons is small.
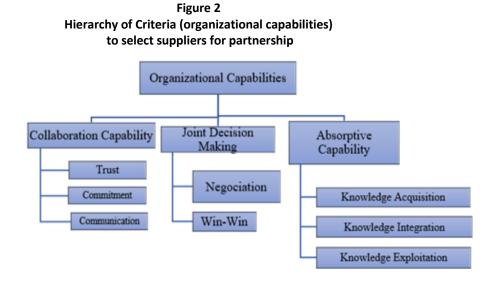
2. Selection. The first activity of this phase is to scan the supplier market to identify potential suppliers and collect information about their capabilities. The specific indicators defined to assess the latent criteria are the inputs of the second activity of the selection process. Different unsupervised quantitative methods may be applied to screen suppliers. In this work, we propose to use the clustering k-means algorithm to categorize suppliers into k ordered groups. This algorithm is one of the most widely used partition-based clustering algorithms and is more computationally attractive than other methods such as c-means, density-based or grid-based algorithms (Azadnia, Saman, Wong, & Hemdi, 2011; Rokach & Maimon, 2005). To identify the "best" cluster, we propose to weight the centroid of each cluster by using the vector $\overrightarrow{GWOC}$ computed in the first phase. Only the suppliers included in the "best" clusters are going to be fully considered to define the final candidates.

3. Post-selection. The last phase of the supplier selection process requires establishing the terms of collaboration, define joint objectives and performance metrics, assign responsibilities and resources, and define communication arrangements. This work is mainly focused in the first two stages of the process; the last stage which deals with the implementation of results through the establishment of long-term partnerships with selected suppliers is out of the scope of this work because it calls for relationship management methods (Lettice et al., 2010).

4. Application to an empirical case

The applicability of the proposed methodology is demonstrated in a case study which involves the selection of strategic suppliers for partnership in the automotive sector. This sector is of particular interest to the Mexican economy because it contributes 2.9% to the national gross product and represents 18.3% of the manufacturing gross product of the country (INEGI & AMIA, 2016). The strategic value of partnerships to face the challenges of the global business environment, improve quality and profitability, and reduce product development lead times has been recognized by main firms in the automotive chain, i.e. automakers and suppliers in the highest level of the chain (Tier 0 or 1, and Tier 2) (Brandes, Brege, & Brehmer, 2013). This justifies our selection of a case study involving major multinational suppliers in the Mexican automotive sector. A detailed description of the two first stages of the selection process follows.

Pre selection stage. A group of four DMs, three supplier managers of automotive firms and an academic expert in MCDM, was integrated. The group validated the structure of the hierarchy of criteria shown in Figure 2. In the third level of the hierarchy there are tangible indicators associated to the latent sub-criteria that represent the dimensions of a particular capability. The validity of these indicators as tangible measures of the supplier's capabilities was previously assessed by (Arroyo-López et al., 2012).

Figure 2
Hierarchy of Criteria (organizational capabilities)
to select suppliers for partnership

To determine the relative importance of one criteria (capability) over another, the DMs expressed their evaluation on the linguistic comparisons scale. Triangular fuzzy numbers (l,m,u) were assigned to these verbal statements to determine the weights or degree of priority of the criteria. These weights were determined by using extent-FAHP and LinPreRa methods. Details of computations for each method are given in sections 4.1 and 4.2.

4.1. Computation of weights with extent-FAHP

Let $A = [a_{ij}]_{n \times n}$ be a triangular fuzzy pairwise comparison matrix, where $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$ represents the linguistic evaluation of capability i against capability j. The entries of the upper part of the matrix are computed as the reciprocal of the fuzzy numbers. The corresponding matrix A of DM1 for the first-level capabilities (FLC) is shown in table 2.

Table 2
Evaluation matrix of DM1 comparing first-level capabilities

DM1	Collaboration Capability			Joint Decision-Making Capability			Absorptive Capability		
	l	m	u	l	m	u	l	m	U
Collaboration Capability	1	1	1	0.14	0.20	0.33	1	3	5
Joint Decision-Making Capability	3	5	7	1	1	1	0.20	0.33	1
Absorptive Capability	0.20	0.33	1	1	3	5	1	1	1

The first step of the fuzzy synthetic extent method is to sum up the rows of the fuzzy comparison matrix using fuzzy arithmetic operations (Chang, 1996) as given in equation [1].

Then, the row sums are normalized applying the correction noticed by Wang and Chen (2008) to get the $\tilde{S}_i$ values of equation [2].

$$RS_i = \sum_{j=1}^{n} a_{ij} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij} \right), i = 1, \dots, n \quad [1]$$

$$\tilde{S}_i = \frac{RS_i}{\sum_{j=1}^{n} RS_i}$$

$$= \left(\frac{\sum_{j=1}^{n} l_{ij}}{\sum_{j=1}^{n} l_{ij} + \sum_{k=1, k \neq i}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{j=1}^{n} u_{ij} + \sum_{k=1, k \neq i}^{n} \sum_{j=1}^{n} l_{kj}} \right) \quad [2]$$

For example, the resulting fuzzy numbers of DM1 regarding the FLC are reported in table 3.

Table 3
DM1 S Values for the FLC

DM1 FLC	Collaboration Capability			Joint Decision-Making Capability			Absorptive Capability		
	I	m	u	I	M	u	I	M	U
RS	2.14	4.20	6.33	4.20	6.33	9.00	2.20	4.33	7.00
$\tilde{S}$	0.118	0.283	0.497	0.240	0.426	0.675	0.123	0.291	0.525

The third step requires computing the degree of possibility between two fuzzy numbers by applying equation [3]:

$$V(\tilde{S}_i \geq \tilde{S}_j) = \begin{cases} 1 & if \ m_i \geq m_j, \\ \dfrac{u_i - l_j}{(u_i - m_i) + (m_j - l_j)} & if \ l_j \leq u_i, \ i,j = 1, \dots, n; j \neq i \quad [3] \\ 0, & otherwise \end{cases}$$

According to Wang et al. (2008), the extent analysis method does not truly determine the degree of possibility of one criterion but to what degree the priority of one decision criterion is bigger than those of all the others in a fuzzy comparison matrix. For the goal of this application, this is sufficient to determine what are the most important capabilities. By using the entries of table 4, Collaboration Capability $(\tilde{S}_i)$ against the Joint Decision-Making Capability $(\tilde{S}_j)$ results in a degree of "possibility" $V(\tilde{S}_i \geq \tilde{S}_j) = 0.642$ By using equation [3] repeatedly, the degree of "possibility" of V_i over all other $(n-1)$ fuzzy numbers is calculated for the n criteria by using equation [4].

$$V(\tilde{S}_i \geq \tilde{S}_j | j = 1,..,n; j \neq i) = \min_{j \in \{1,...,n\}, j \neq i} V(\tilde{S}_i \geq \tilde{S}_j), \qquad i = 1, ..., n \qquad [4]$$

For example, for the JDM criterion we have $V(\tilde{S}_1 \geq \tilde{S}_2, \tilde{S}_3) = min(V(S_1 \geq S_2), V(S_1 \geq S_3)) = min(0.642, 0.976) = 0.642$. The degrees of "possibility" of all criteria are shown in the second column of table 4. The final weights for the FLC are reported in the last column of table 4 are computed by normalization of the V values.

Table 4
Weights of importance of FLC of DM1

Criterion1	V	W'
Collaboration Capability	0.642	0.277
Joint Decision-Making Capability	1	0.431
Absorptive Capability	0.679	0.293

The same procedure is applied to the fuzzy comparison of the other DMs to get the group vector of weights $\overrightarrow{GWOC}$ = (0.319, 0.358, 0.323). Applying the same process to the sub-criteria at the second level of the hierarchy, i.e. the capability dimensions we obtain the weights shown in the last column of table 5.

Table 5
Group Weights for Organizational Capabilities
Computed with Extent-FAHP

FLC	FLC Weight	Sub-Criteria	SLC Weight	$\overrightarrow{GWOC}$
Collaboration Capability	0.319	Trust	0.213	0.068
		Commitment	0.283	0.090
		Communication	0.503	0.161
Joint Decision-Making Capability	0.358	Negotiation	0.25	0.089
		Win-Win	0.75	0.268
Absorptive Capability	0.323	Knowledge Acquisition	0.213	0.069
		Knowledge Integration	0.000	0.000
		Knowledge Exploitation	0.805	0.260

4.2. Computations of weights with LinPreRa

Not all pairwise evaluations a_{ij} (for all i≠j) are required when using LinPreRa, which is an advantage when there are many criteria under comparison. In the case of the first-level criteria, only a_{21} and a_{32} are needed. Following

the procedure described by Chen, Wang and Wu (2011) we apply the transformation function given in equation [5] to each pairwise comparison available.

$$p_{ij} = g(a_{ij}) = \frac{1}{2}(1 + log_{11}a_{ij}) \qquad [5]$$

For example, the linguistic evaluation when comparing the Joint Decision-Making capability (i=2) against the Collaborative capability (j=1) was fairly strong, thus the associated fuzzy numbers are [3,5,7]. After applying transformation [5] we get $p_{21}^l = 0.729; \; p_{21}^m = 0.836; \; p_{21}^u = 0.906.$ To estimate the missing pairwise comparisons, proposition 2.3.2 stated by Chen et al. (2011, p. 1325) to assure a consistent reciprocal fuzzy linguistic preference relation needs to be used. The following fuzzy numbers result:

$$p_{13}^l = 1.5 - p_{32}^u - p_{21}^u = 1.5 - 0.836 - 0.906 = -0.241$$

$$p_{13}^m = 1.5 - p_{32}^m - p_{21}^m = 1.5 - 0.729 - 0.836 = -0.065$$

$$p_{13}^u = 1.5 - p_{32}^l - p_{21}^l = 1.5 - 0.500 - 0.729 = 0.271$$

Then, proposition 2.3.1 (Chen, Wang and Wu, 2011, p. 1325) corresponding to a fuzzy reciprocal multiplicative preference is applied to obtain the remaining fuzzy numbers. To prevent negative fuzzy numbers, the transformation $\frac{x+c}{1+2c}$ (Wang & Chen, 2008) is used. The resulting fuzzy numbers $\tilde{\tilde{p}}_{ij}$ associated to the FLC of DM1 are shown in table 6.

Table 6
DM1 First Level Criteria Evaluation Matrix

DM1 FLC	Collaboration Capability			Joint Decision-Making Capability			Absorptive Capability		
	l	m	u	l	m	u	l	m	u
Collaboration Capability	0.500	0.500	0.500	0.226	0.274	0.345	0.000	0.119	0.345
Joint Decision-Making Capability	0.655	0.726	0.774	0.500	0.500	0.500	0.274	0.345	0.500
Absorptive Capability	0.655	0.881	1.000	0.500	0.655	0.726	0.500	0.500	0.500

Once the fuzzy numbers are computed, the linguistic averaging operator given in equation [6] is calculated to get the criteria weights using equation [7].

$$\tilde{A}_i = \frac{\sum_{j=1}^{n} \tilde{\tilde{p}}_{ij}}{n} \quad i = 1,2,\dots,n \; and \; j = 1,2,\dots,n \qquad [6]$$

$$\tilde{W}_i = \frac{\tilde{A}_i}{\sum_{i=1}^{n} \tilde{A}_i} \qquad [7]$$

The $\tilde{A}_i$ (i = 1, 2, 3) values and corresponding weights of the first level criteria of DM1 are reported in the second and third column of table 7 respectively. Following the same procedure, we get the normalized weights of the second-level criteria shown in the last column of the table 7.

Table 7
LinPreRa FLC and SLC Weights for the DM1

FLC	FLC $\tilde{A}_i$	FLC $\widetilde{W}_i$	SLC	SLC $\tilde{A}_i$	SLC $\widetilde{W}_i$
Collaboration Capability	0.937	0.21	Trust	1.114	0.248
			Commitment	1.930	0.429
			Communication	1.455	0.323
Joint Decision-Making Capability	1.591	0.35	Negotiation	1.272	0.636
			Win-Win	0.727	0.363
Absorptive Capability	1.972	0.44	Knowledge Acquisition	2.250	0.491
			Knowledge Integration	1.167	0.254
			Knowledge Exploitation	1.165	0.254

Finally, the group weights of first level-criteria $\overrightarrow{GWOC_{FLC}}$ are simply computed as the average of the weights $\widetilde{W}_i$

of each DM. The group vector of weights for the second-level criteria $\overrightarrow{GWOC_{SLC}}$ is obtained by multiplying the average of the individual second-level weights by the weight of the first-level criterion. Results are shown in table 8.

Table 8
Final Group Weight for Organizational
Capabilities according to LinPreRa

FLC	DM1	DM2	DM3	DM4	$\overrightarrow{GWOC_{FLC}}$	
Collaboration Capability	0.210	0.284	0.479	0.415	0.347	
Joint Decision-Making Capability	0.352	0.479	0.333	0.170	0.334	
Absorptive Capability	0.438	0.237	0.188	0.415	0.319	
SLC (**Collaboration Capability**)	DM1	DM2	DM3	DM4	W	$GWOC_{SLC}$
Trust	0.248	0.438	0.188	0.188	0.266	0.092
Commitment	0.429	0.352	0.333	0.333	0.361	0.125
Communication	0.323	0.210	0.479	0.479	0.373	0.129
SLC (**Joint Decision-Making Capability**)	DM1	DM2	DM3	DM4	W	
Negotiation	0.636	0.316	0.316	0.316	0.396	0.132
Win-Win	0.363	0.684	0.684	0.684	0.604	0.202
SLC (**Absorptive Capability**)	DM1	DM2	DM3	DM4	W	
Knowledge Acquisition	0.491	0.308	0.496	0.210	0.376	0.120
Knowledge Integration	0.254	0.292	0.246	0.333	0.281	0.090
Knowledge Exploitation	0.254	0.400	0.259	0.456	0.342	0.109

As previously noted by Chen et al. (2011) LinPreRa method reduces the number of pairwise comparisons and prevents inconsistent comparisons, thus increasing decision making efficiency and accuracy. In this study, we use both methods and compare the weights of criteria (organizational capabilities) and sub-criteria (dimensions of each capability) determined by each one. Comparisons were made based on the percentage difference between weights, computed as the ratio of the difference between weights (in absolute value) divided by its simple average. In the case of the main dimensions or criteria, the geometric mean equals 6.9% and the median is 4.18%, thus indicating a low variability between the weights determined with both methods. Regarding the sub-criteria, the maximum difference of 74% between weights corresponds to the sub-dimension of "knowledge exploitation". The geometric mean of the percentage differences of the sub-dimensions is 39.1%. If outliers are deleted -knowledge exploitation and knowledge integration because a "0" weight was computed with extant FAHP-, the geometric mean equals 35.1% and the median is 38.8% which are considered reasonable based on the statistical criteria of a relative variation around 30%. Thus, confirming both methods provide similar weights but LinPreRa is easier to use (Chen et al., 2011).

4.3. Selection of potential suppliers

Data collected by Arroyo, De Boer and Holmen (2012) through an e-mail survey administered to strategic suppliers of lead firms (automakers or first-tier suppliers) of the automotive sector in Mexico was used. Only the information of the indicators related to supplier's capabilities for partnership is used as input of the present study. The total sample size is 54 suppliers, most of them medium to large manufacturers (70%). The majority of participants (37%) were tier-one suppliers interested in sustaining partnerships with other tier-one suppliers, or tier-2 and tier-3 suppliers that source a unique or basic component.

The screening of suppliers is accomplished by using the k-means algorithm; the inputs of the method are the supplier's scores on each sub-criterion computed as the average of the tangible indicators comprising the sub-criterion. We use the elbow method to define the number of clusters; a solution with more than four clusters resulted in a small decline of the sum of squared distance between data points and their assigned cluster's centroids (James, Witten, Hastie, & Tibshirani, 2013). Therefore, a solution with k = 4 clusters resulted appropriate, then we computed the centroids of the four clusters reported in table 9.

Table 9
Cluster Centroids

ID	K1	K2	K3	K4
Trust	0.374	0.464	0.306	0.129
Commitment	0.333	0.667	0.472	0.000
Communication	0.543	0.505	0.330	0.177
Negotiation	0.403	0.781	0.408	0.108
Win-Win	0.533	0.683	0.302	0.139
Knowledge Acquisition	0.532	0.525	0.384	0.376
Knowledge Integration	0.691	0.536	0.325	0.396
Knowledge Exploitation	0.251	0.733	0.553	0.397

To select the best set of suppliers, each cluster centroid (K) is multiplied by the vector of importance weights $\overrightarrow{GWOC}$ previously computed either using the extent FAHP method (section 4.1) or LinPreRa (section 4.2). The

weighted scores and ranks for each of the four clusters are the entries of table 10. The differences between rankings (as percentage of variation) is negligible. With both methods, cluster 2 has the best (highest) rank, therefore, the suppliers in this cluster {0,3,7,9,12,20,39,45,52} are the most suitable candidates for partnership.

Table 10
Cluster Evaluation Comparison

Cluster	CCW FAHP	CCW LinPreRa	Percentual difference
K1	0.424	0.461	8%
K2	**0.653**	**0.624**	**5%**
K3	0.404	0.381	6%
K4	0.213	0.201	6%

Before establishing any relationship (last stage of the supplier selection process described in Figure 1) audits or visits in-situ to pre-selected suppliers are recommended to validate their capabilities for partnerships. Because cross-validation of organizational capabilities could be very resource-consuming, the filtering of suppliers is convenient to reduce the cost and complexity of the capabilities' assessment. Moreover, several projects may be developed simultaneously to increase the proportion of shared resources in order to develop new solutions for processes and projects. Therefore, ranking suppliers is not the main interest of the proposed methodology.

5. Conclusions and implications

The selection of reliable, collaborative and trustworthy suppliers is a difficult task for organizations because there are many suppliers' criteria to be considered and usually no single supplier satisfies the organization requirements. Therefore, MCDM methods provide a proper approach for organizations that are looking for a satisfactory solution. In this study we propose a methodology to screen potential suppliers whose capabilities facilitate the development of collaborative projects with the customer. Very well-known and easy to implement methods are used to compute the relative importance of three capabilities for partnership and then a clustering algorithm is applied to group suppliers into ordered clusters. The application of the proposed methodology to a case study shows LinPreRa and extent-FAHP produce similar results but LinPreRa has some practical advantages such as the reduction in the number of pairwise comparisons required to compute the comparison matrix and the guarantee of no inconsistencies between comparisons.

The two aforementioned methods have been found to be not very reliable in the determination of the weights used to rank alternatives (Wang, Luo, & Hua, 2008) but the purpose of their application is not to find the final suppliers' rankings but to identify the most promising suppliers. Once they are recognized, further screening may be done to gather more information about the relationship capabilities of these suppliers. In the case study described in this research, the initial number of suppliers was 54 and the final set of pre-selected suppliers is only 7 which considerably reduces the number of suppliers that may be considered to participate in collaborative projects.

Sixty percent of the interviewed suppliers (33) source two large Tier-1 suppliers located in the North part of Mexico. Technical reports including only the data of the suppliers of each manufacturer were elaborated and submitted to the supplier manager of each company. One of the managers used the results to provide feedback to the least capable suppliers while the other company developed joint projects with two of the suppliers of the

"best" qualified cluster. These actions show how the results of this work can be applied. However, to our knowledge none of the two companies implemented the proposed methodology as a standardized technique to select potential candidates for long-term partnership. Organizations are sometimes reluctant to the use of quantitative decision-making methods because they judge them complex and costly. But all computations required by the two suggested methodologies, fuzzy LinPreRa and FAHP, may be performed with the help of low-cost and easy-to-use available tools such as Excel. Regarding k-means, statistical commercial software, for example MINITAB and SPSS, may be used to filter suppliers. The use of a free software of wide purposes such as R offers an attractive option to implement the suggested methodology as well as to design a customized decision-support system to solve other MCDM problems. Moreover, because LinPreRa provides similar results to extent-FAHP, but it is easier to apply because it significantly reduces the number of pairwise comparisons required and prevents inconsistences and zero weights. Therefore, organizations would find it attractive to organize their judgments and support their decisions. Unfortunately, managerial attitudes, the necessity of prompt decisions and the absence of timely and reliable data, are major barriers for the implementation of systematic methodologies for group supplier selections.

Extensions of this research include the application of the proposed methodology to solve similar multicriteria decision making problems such as personnel and project selection. In terms of basic research, possible extensions include: the development of new clustering algorithms that partition the data into ordered clusters which consider the preference degree between any two criteria and the proposal of new methods to combine the individual judgements of decision makers.

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