Expert Systems With Applications 79 (2017) 53–64

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

# A model based on 2-tuple fuzzy linguistic representation and Analytic Hierarchy Process for supplier segmentation using qualitative and quantitative criteria

Luiz Felipe de Oliveira Moura Santos[a], Lauro Osiro[b,*], Rafael Henrique Palma Lima[c]

[a] Production Engineering Department, University of São Paulo, São Paulo, SP, Brazil
[b] Production Engineering Department, Federal University of Triangulo Mineiro, Uberaba, MG, Brazil
[c] Production Engineering Department, Federal University of Technology Paraná, Londrina, PR, Brazil

ARTICLE INFO

*Article history:*
Received 23 August 2016
Revised 16 February 2017
Accepted 20 February 2017
Available online 21 February 2017

*Keywords:*
Supply chain management
Supply segmentation
AHP
2-tuple linguistic representation model

ABSTRACT

The literature on supply base segmentation has increasingly adopted multi-criteria decision making (MCDM) techniques into recently proposed models. However, most proposals segment the supply base from the standpoint of the purchased item, which prevents them from providing guidelines that are specific to each supplier. Some authors have attempted to overcome these limitations by putting forward portfolio models based on the relationship with suppliers. These approaches use fuzzy variables and MCDM methods that take qualitative judgements by experts as the only input for decision making. However, many companies have databases with historical data about the performance of past transactions with suppliers that should be considered by expert systems that aim to comprehensively evaluate suppliers' performance. This paper seeks to address this gap by proposing a segmentation model based on the relationship with suppliers capable of aggregating quantitative and qualitative criteria. Analytic Hierarchy Process (AHP) was used to determine the relative importance of each criteria. Fuzzy 2-tuple, a prominent computing with word (CWW) approach, was used to evaluate suppliers with a mixture of historical quantitative data and qualitative judgements by purchasing experts. An illustrative application of the proposed model was carried out in the pharmaceutical supply center (PSC) of a teaching hospital. The proposed model can be viewed as a decision support system capable of aggregating the qualitative judgements of experts and quantitative historical performance measures, thus providing guidelines to improve the relationship between suppliers and the buyer firm.



## 1. Introduction

The participation of suppliers in the cost and value proposition of products has increased over the past few decades (Prajogo, Chowdhury, Yeung, & Cheng, 2012). Hence, supply management needs to be aligned with and contribute to the strategic objectives of the buyer firm (Abdollahi, Arvan, & Razmi, 2015; González-Benito, 2007). This process has to be efficient and well-structured because it consumes the firm's limited resources (Krause, 1997). According to Dyer, Cho, and Chu (1998), the segmentation of the supplier base, which consists in grouping together suppliers according to their similarities, is tantamount to any organization seeking to properly manage its supply process. Researchers and practitioners have emphasized the use of purchasing portfolio models for managing the supplier base due to their simplicity and effectiveness (Drake, Lee, & Hussain, 2013; Dubois & Pedersen, 2002; Gelderman & Weele, 2003).

The first purchasing portfolio model was introduced by Parasuraman (1980), who stablished a rational connection between consumer market and supplier base segmentation. The model, however, did not determine relevant variables for supplier segmentation. Kraljic (1983) addressed this gap by developing a practical purchasing portfolio model based on the purchased item's characteristics. The model has two dimensions that cover aspects that are both internal and external to the buyer firm. The internal criteria refer to the impact of the supplied item over the final product's cost and quality. External criteria are associated with supply risk and address issues as the number of potential suppliers and the bargaining power of suppliers. The combination of low and high levels of these dimensions results in four categories of purchased items: non-critical routine items (low impact and low risk), leverage items (high impact and low risk), bottleneck items (low

* Corresponding author.
*E-mail addresses:* luiz.fel.moura@usp.br (L.F.d.O.M. Santos), lauro@icte.uftm.edu.br, lauro.osiro@sc.usp.br (L. Osiro), rafaelhlima@utfpr.edu.br (R.H.P. Lima).

http://dx.doi.org/10.1016/j.eswa.2017.02.032
0957-4174/

impact and high risk) and strategic items (high impact and high risk). The model introduced by Kraljic (1983) is regarded in the literature as the most influential purchasing portfolio model (Caniels & Gelderman, 2007; Day, Magnan, & Munkgaard, 2010; Luzzini, Caniato, Ronchi, & Spina, 2012; Osiro, Lima-junior, & Carpinetti, 2014; Rezaei & Ortt, 2013a).

Other theoretical models based on internal and external dimensions were put forward by Nellore and Soderquist (2000); Olsen and Ellram (1997) and Pagell, Wu, and Wasserman (2010). In addition, several studies such as Ferreira, Arantes, and Kharlamov (2014), Lee and Drake (2010), Luo, Wu, Rosenberg, and Barnes (2009), Padhi, Wagner, and Aggarwal (2012), and Segura and Maroto (2017) used multi-criteria techniques to evaluate and aggregate the various criteria of these two dimensions and ultimately serve as a tool for supplier base assessment.

The segmentation based solely on the characteristics of the supplied item does not provide guidance on how suppliers of items of the same category, but with different performance levels, should be developed (Dubois & Pedersen, 2002; Rezaei & Ortt, 2012). According to Day et al. (2010), portfolio approaches should involve the analysis of buyer-supplier relationship to more effectively guide supplier development and value creation initiatives. In this sense, approaches that seek to analyse the buyer-supplier relationship, such as Bensaou (1999), Olsen and Ellram (1997) and Rezaei and Ortt (2012) have gained relevance.

Rezaei and Ortt (2012) developed a supplier portfolio model that has been combined with various multi-criteria decision making (MCDM) approaches. In order to focus on the long-term relationship between the buyer and its suppliers, the model has two dimensions: (i) supplier capabilities and (ii) supplier willingness to cooperate. The authors define supplier capabilities as the "*complex bundles of skills and accumulated knowledge, exercised through organizational processes that enable firms to co-ordinate activities and make use of their assets in different business functions that are important for a buyer*", whereas supplier willingness to cooperate refers to the "*confidence, commitment and motivation to engage in a (long-term) relationship with a buyer*".

When implementing a portfolio model, the buyer firm may choose multiple criteria to constitute each dimension. Some of them may be quantitative, thus deriving from numerical data concerning previous transactions between both parties. With the rise of information technologies as big data and the wide adoption of organizational information systems, companies now have databases with historical data concerning past transactions with suppliers. Such data can be compiled into quantitative performance measures that should be combined with qualitative assessment by purchasing experts to more comprehensively support decision making in the supply base management (Segura & Maroto, 2017). However, the approaches that build on Rezaei and Ortt's (2012) portfolio model, based on fuzzy variables and MCDM methods, rely solely on the decision maker's judgement to evaluate all criteria. Historical performance indicators with quantitative data have yet not been added to these approaches.

Supplier selection and evaluation is regarded in the literature as a very complex activity because it involves multiple criteria and often rely on experienced staff (Ho, Xu, & Dey, 2010; Sarkis & Talluri, 2002). Additionally, decisions regarding supplier selection and evaluation need to be made routinely, thus demanding considerable efforts by the purchasing department (Krause, Handfield, & Scannell, 1998). This calls for the development of expert systems, whose purpose is to model the knowledge of human experts and use computerized methods to replicate their decisions (Liao, 2005). Henceforth, the adoption of such decision support systems might improve efficiency of the supplier evaluation and selection processes, making them faster and enabling more complex analyses such as portfolio models to be conducted.

The literature on expert systems for supplier evaluation and selection is very complex, with the proposition of a wide variety of methods. Soft computing and artificial intelligence techniques such as fuzzy logic, neural networks, AHP, ANP (Analitic Network Process), TOPSIS and others MCDM methods have often been integrated in various configurations to propose new methods to evaluate, segment and select suppliers (Chai, Liu, & Ngai, 2013; Govindan, Rajendran, Sarkis, & Murugesan, 2015).

The supplier portfolio models based on supplier capabilities and willingness to cooperate found in the literature require great efforts by experts during the knowledge modelling phase. For example, Rezaei and Ortt (2013a) proposed the use of fuzzy rule-based systems, also known as fuzzy inference systems – FIS, to assess the two dimensions. In the evaluation of each criterion, the decision makers use scores ranging from 1 to 5 for their judgment. The greatest hurdle of this approach is the large number of rules that have to be created. Preference relations-based fuzzy AHP (Analytic Hierarchy Process) is used by Rezaei and Ortt (2013b) to evaluate the criteria. In their application, they used six criteria to evaluate supplier capabilities and another six criteria to evaluate supplier willingness to cooperate. The role of AHP is to determine the weights of the criteria in both dimensions. This lead to a consistent priority-ranking with experts having to make only $(n^2 - n)/2$ pairwise comparisons.

More recently, Rezaei, Wang, and Tavasszy (2015) proposed the application of a new MCDM method known as Best Worst Method to segment suppliers using their portfolio matrix. In their work, the evaluation of criteria aggregated in both dimension is based on judgments of experts. The weights of the criteria are defined after the decision makers conduct pairwise comparisons between the best criterion and the remaining criteria and between the worst criterion and the other criteria.

Osiro et al. (2014) proposed a fuzzy logic approach to supplier evaluation and development that has two matrices. The first classifies the purchased items and the second is used to evaluate the suppliers. The dimensions of the second matrix are delivery performance and potential for partnership, which are analogous to the dimensions used by Rezaei and Ortt (2012). Again, the evaluation of all the criteria derive from experts' judgements. The decision makers use scores ranging from 1 to 10 for their judgments and three linguistic terms are used in the fuzzification process.

It is also worth noting that the aforementioned supplier segmentation approaches did not include performance indicators with quantitative data. These approaches focused only on modeling knowledge and reaching consensus among the actors involved with the supply process. They did so with qualitative judgements made by experts as the only means to evaluate suppliers. The aim of this paper is thus to address this gap by presenting a new model for supplier segmentation that combines experts' judgements and quantitative historical data in the assessment of the supplier base. In this manner, evaluation criteria for both Rezaei and Ortt's (2012) dimensions "supplier capabilities" and "supplier willingness to cooperate" can take advantage of data stored in databases with historical information about the performance of suppliers.

The method proposed in this paper is based on two techniques: AHP and 2-tuple linguistic representation. AHP is used only to determine the relative weights of the criteria in both dimensions of the portfolio matrix. In a traditional AHP application, further pairwise comparisons would have to be carried out to compare all suppliers in each criterion. Even with a small number of suppliers, this would lead to a huge number of pairwise comparisons. Also, if suppliers are added or removed, all pairwise comparisons would need to be updated, which would make the supplier evaluation process rather cumbersome. The use of 2-tuple linguistic representation (Herrera & Martinez, 2000a) allows for a more flexible and efficient supplier evaluation system, because it does not require pairwise comparisons among all suppliers for each criterion. Instead, it aggregates quantitative and qualitative evaluations for each supplier directly and yields performance measures that can be used to rank suppliers. Fuzzy 2-tuple linguistic representation has been widely used in decision support systems (Martínez & Herrera, 2012). In the specialized literature, there are some applications of 2-tuple for supplier selection (Karsak & Dursun, 2015; You et al., 2015; Wen, Yan, Xian, Yue, & Peng, 2016; Cid-López, Hornos, Carrasco, & Herrera-Viedma, 2016; Qin and Liu, 2016), but none of them use portfolio models to evaluate the performance of suppliers.

The remainder of this paper is organized as follows. Section 2 briefly reviews the subject of supplier assessment criteria. Section 3 introduces the AHP method used in the proposed model. Section 4 presents the fundamentals of fuzzy 2-tuple representation of sets of linguistic terms. Section 5 describes the proposed model for supplier assessment followed by an illustrative application in a hospital's pharmaceutical supply center. Section 6 discusses the results and its implications on the proposed model. Finally, Section 7 presents some final remarks as well as directions for future research.

## 2. Supplier assessment criteria

The process of evaluating and selecting suppliers usually involves a variety of criteria (Cheraghi et al., 2004; Ho et al., 2010). The seminal work of Dickson (1966) lists 23 criteria used to select and evaluate suppliers. Since then, many researchers have addressed the topic of how to make better decisions in the supply process. Initially, more emphasis was given to quantitative criteria. For example, Dempsey (1978) uses criteria related to operational efficiency such as price, compliance with requirements and delivery.

Weber, Current, and Benton (1991) took on the Just in Time philosophy and included some less tangible criteria as production facilities and technical capabilities among the most relevant criteria for supplier evaluation. Ellram (1990) used the term *hard* to classify easily measurable quantitative criteria such as costs, nonconformities and service level, whereas *soft* criteria encompassed aspects such as strategic alignment and commitment. According to Kannan and Tan (2002), managers must pay special attention to soft criteria in evaluating strategic suppliers with long-term relationships. Despite the importance of hard criteria, the authors contend that soft criteria exert more influence on the buyer's market share and return over investment.

Various criteria have been included in the approaches for supplier selection and evaluation found in the literature. Techniques as AHP and methods based on fuzzy variables enable the determination of numerical values for soft criteria based on the perceptions of experts (Chai et al., 2013; Ho et al., 2010). That explains why many models rely solely on the judgements and perceptions of decision makers (Liao et al., 2014; Osiro et al., 2014; Rezaei et al., 2015). However, hard criteria should not be cast aside. The supplier base should instead be systematicaly assessed using a combination of hard and soft criteria (Dyer et al., 1998; Gunasekaran; Kobu, 2007; Lockström et al., 2010). Tables 1 and 2 outline criteria commonly associated with supplier capabilities and willingness to cooperate, respectively.

## 3. Analytic hierarchy process

The Analytic Hierarchy Process (AHP) was proposed by Saaty (1988) to solve multi-criteria decision making (MCDM) problems by means of pairwise comparisons to extract the preferences of experts with regard to a set of criteria or alternatives. Since its inception, AHP has been applied to a variety of problems such as facility location, project management, investment portfolio, among others (Brunelli, 2015; Subramanian & Ramanathan, 2012; Vaidya & Kumar, 2006). Tramarico et al. (2015) carried out a bibliometric study and found 116 papers that address supply chain problems with AHP, such as vendor selection, purchasing strategies, vendor rating, performance measurement and green supply chain development.

One of the main strengths of AHP is its ability to deal with subjective opinions of experts and derive a quantitative priority vector that describes the relative importance of each alternative, which makes AHP appealing to a wide variety of MCDM problems (Subramanian & Ramanathan, 2012). Some authors contend that the applicability of AHP can be attributed to its simplicity, ease of use, flexibility as well as the possibility of integrating AHP with other techniques such as fuzzy logic and linear programming (Ho, 2008).

The first step in an AHP application is the determination of which criteria describes the decision being made. Let $n$ be the number of criteria in a particular problem, then the second step is to request an expert to evaluate each pair of criteria. If $i$ and $j$ are two criteria under evaluation, then the expert needs to assign a value $a_{ij}$ corresponding to the relative importance of $i$ against $j$. The numerical scale in Table 3 is often used for this task.

As an example, if $a_{ij} = 5$ for a pair of criteria $i$ and $j$, this would mean that criterion $i$ is strongly more important than criterion $j$. Conversely, the relative importance of criterion $j$ with respect to $i$ would be $a_{ji} = 1/5$. This is known as the reciprocity rule in AHP comparison matrices, hence $a_{ji} = 1/a_{ij}$ for any given pair of criteria $i, j = 1 \dots n$. Additionally, for any $i = 1 \dots n$, criterion $a_{ii} = 1$. The matrix shown in Eq. (1) depicts how data is organized after all pairwise comparisons have been made.

$$A = \left[a_{ij}\right] = \begin{pmatrix} 1 & a_{12} & a_{13} & \cdots & a_{1n} \\ 1/a_{12} & 1 & a_{23} & \cdots & a_{2n} \\ 1/a_{13} & 1/a_{23} & 1 & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & 1/a_{3n} & \cdots & 1 \end{pmatrix} \tag{1}$$

The next step is to use the comparison matrix to calculate the relative importance of each criteria. This paper uses the geometric mean method, as described by Crawford (1987), which is widely used in the literature (Brunelli, 2015). Eq. (2) can be used to calculate the relative weight $w_i$ of the $i$th criterion.

$$w_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}} \Big/ \sum_{k=1}^{n} \left(\prod_{j=1}^{n} a_{kj}\right)^{\frac{1}{n}} \tag{2}$$

The final step is to determine whether the comparison matrix is consistent. This is an important step of AHP to ensure that comparisons are coherent and have not been made at random. Eq. (3) shows how to calculate the consistency index of the comparison matrix $A$, expressed as $CI(A)$.

$$CI(A) = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

In Eq. (3), $\lambda_{max}$ is the maximum eigenvalue of matrix $A$. In this paper, we estimate $\lambda_{max}$ using Eq. (4).

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{w_j a_{ij}}{w_i} \tag{4}$$

Finally, Eq. (5) can be used to calculate the consistency ratio, which is the ratio between $CI(A)$ and a random index $RI_n$ that varies according to the number of criteria $n$.

$$CR = \frac{CI(A)}{RI_n} \tag{5}$$

**Table 1**
Criteria associated with supplier capabilities.

| Criteria | Related work |
|---|---|
| **Billing and order processing system** | Dickson (1966); Weber et al. (1991) |
| **Costs control** | Kannan and Tan (2002); Weber et al. (1991) |
| **Delivery reliability** | Dickson (1966); Fisher (1997); Ho et al. (2010); Krause (1997) |
| **Development capabilities** | Dyer et al. (1998); Ho et al. (2010); Lima, Osiro, and Carpinetti (2013) |
| **Historical performance** | Dempsey (1978); Dickson (1966) |
| **Impact on profit** | Dyer et al. (1998); Kraljic (1983) |
| **Industrial knowledge** | Dempsey (1978); Weber et al. (1991), Kannan and Tan (2002) |
| **Innovation** | Fisher (1997); Nellore and Söderquist (2000) |
| **Lead time** | Rezaei and Ortt (2012); Rezaei et al. (2015) |
| **Location/proximity** | Bensaou (1999); Kannan and Tan (2002); Weber et al. (1991) |
| **Management and organization** | Ho et al. (2010); Olsen and Ellram (1997); Weber et al. (1991) |
| **Market knowledge** | Fisher (1997); Hilletofth (2012) |
| **Packaging capabilities** | Dickson (1966); Rezaei and Ortt (2012); Weber et al. (1991) |
| **Post-sales support** | Dempsey (1978); Dickson (1966) |
| **Previous transactions** | Dickson (1966); Weber et al. (1991) |
| **Price/cost** | Dickson (1966); Dweiri, Kumar, Khan, and Jain (2016); Fisher (1997); Ho et al. (2010) |
| **Product quality** | Dempsey (1978); Dweiri et al. (2016); Dyer et al. (1998); Ho et al. (2010) |
| **Product reliability** | Rezaei et al. (2015); Shin, Collier, and Wilson (2000) |
| **Production, manufacturing, facilities and capacity** | Bensaou (1999); Dyer et al. (1998) |
| **Project capabilities** | Aydın Keskin, İlhan, and Özkan (2010); Nellore and Söderquist (2000) |
| **Responsiveness** | Kannan and Tan (2002); Olsen and Ellram (1997) |
| **Technical capabilities** | Dempsey (1978); Ho et al. (2010); Kannan and Tan (2002) |
| **Technologies** | Bensaou (1999); Kraljic (1983); Nellore and Söderquist (2000) |

**Table 2**
Criteria associated with willingness to cooperate.

| Criteria | Related work |
|---|---|
| **Commitment to continuous improvement** | Dyer and Nobeoka (2000); Krause (1997) |
| **Commitment to quality** | Krause (1997); Lima et al. (2013); Olsen and Ellram (1997) |
| **Compliance with procurement procedures** | Weber et al. (1991) |
| **Coordination of product development** | Dyer et al. (1998); Nellore and Söderquist (2000) |
| **Ethics, mutual respect and honest** | Dyer et al. (1998); Govindan, Kannan, and Haq (2010) |
| **Honest and frequent communication** | Dyer et al. (1998); Kannan and Tan (2002); Lima et al. (2013) |
| **Impression** | Dickson (1966); Weber et al. (1991) |
| **Mutual respect and honesty** | Ho et al. (2010); Kannan and Tan (2002) |
| **Openness to frequent and honest communication** | Dyer and Nobeoka (2000); Dyer et al. (1998); Krause (1997) |
| **Previous experiences with supplier** | Nellore and Söderquist (2000); Weber et al. (1991) |
| **Reciprocal agreements** | Dickson (1966); Olsen and Ellram (1997) |
| **Relationship proximity** | Dyer and Nobeoka (2000); Lima et al. (2013) |
| **Specific investments** | Bensaou (1999); Dyer et al. (1998) |
| **Transparency** | Dyer and Nobeoka (2000); Rezaei et al. (2015) |
| **Willingness for long term commitment** | Bensaou (1999); Dyer et al. (1998) |
| **Willingness to share information** | Dyer and Nobeoka (2000); Fisher (1997); Olsen and Ellram (1997) |

**Table 3**
Numerical values for criteria evaluation (Saaty, 1990).

| Numerical value | Definition | Explanation |
|---|---|---|
| 1 | Equal importance | Both criteria contribute equally to the objective |
| 3 | Moderate importance of one over another | Experience and judgement slightly favor one criterion over another |
| 5 | Essential or strong importance | Experience and judgement strongly favor one criterion over another |
| 7 | Very strong importance | One criterion is favored very strongly and its dominance is demonstrated in practice |
| 9 | Extreme importance | The evidence favoring one criterion over another is of the highest possible order of affirmation |
| 2, 4, 6 and 8 | Intermediate values | These values are used when compromise in needed |

Table 4 shows values for $RI_n$ developed by Saaty (1990) for $n$ ranging from 1 to 10. As a rule of thumb, if $CR < 0.1$, then the comparison matrix is considered to be sufficiently consistent and the relative weights reflect the expert's preferences expressed in the comparison matrix.

**Table 4**
$RI_n$ values for $n = 1 \ldots 10$.

| $n$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| $RI_n$ | 0 | 0 | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

## 4. Fuzzy 2-tuple representation of linguist term sets

The approach known as 2-Tuple, which stems from the Computing With Word (CWW) field, is a fuzzy linguistic representation model proposed by Herrera and Martinez (2000a) that uses aggregation operators without loss of information. The method works differently than solutions based on symbolic methods or the extension principle. The 2-Tuple approach represents linguistic information by means of a pair of values ($s_i$, $\alpha$), where $s_i$ is a linguistic term and $\alpha$ is a numeric value representing the symbolic translation. The value $s_i$ belongs to the pre-defined linguistic term set $S$ and represents the linguistic label's center of the information. The term $\alpha$ expresses the value of the translation from the original result of an aggregation operation $\beta$ to the closest index label $i$ in the linguistic term set $S$. Hence $\alpha$ is called the symbolic translation.

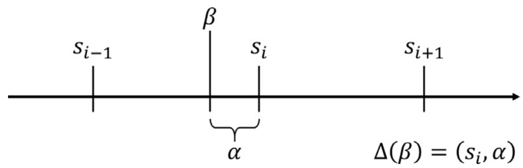


**Fig. 1.** How $\beta$ determines the closest label $s_i$ and the symbolic translation $\alpha$.

Let $S = \{s_0, \cdots, s_g\}$ be a linguist term set and $\beta \in [0, g]$ be the result of an aggregation operation, then the representation of $\beta$ in 2-Tuple can be obtained with Eq. (6).

$$\Delta(\beta) = (s_i, \alpha) \tag{6}$$

With

$$\begin{cases} s_i, \ \ i = round(\beta) \\ \alpha = \beta - i, \ \ \alpha \in [-0.5, 0.5), \end{cases} \tag{7}$$

The expression $round(\beta)$ is the usual round operation, so the label $s_i$ has the closest index to $\beta$; $\alpha$ is a value in the interval $[-0.5, 0.5)$ representing the symbolic translation. Fig. 1 shows how the value $\alpha$ represents the information difference between the aggregation result $\beta$ and the closest linguistic term $s_i$. The main advantage of 2-tuple representation is that it is continuous in its domain, thus avoiding the loss of information and lack of precision in the aggregation process.

According to Herrera and Martinez (2000b), any quantitative variable can be represented by linguistic 2-tuples without any loss of information, provided that $S$ satisfies 3 conditions and that the quantitative variables are normalized to $\vartheta \in [0, 1]$.

Let $S = \{s_0, \cdots, s_g\}$ be a linguistic term set that satisfies the following conditions:

1. $S$ is a fuzzy partition, i.e., with $X = [0, 1]$, we have $\sum_{i=1}^{g} \mu_{s_i}(x) = 1, \ \forall x \in X$.
2. The membership functions of all its terms are triangular, i.e., $s_i = (a_i, b_i, c_i)$.
3. The maximum degree of membership $b_i$ that corresponds to the membership function of the characteristic value is equal to 1. In other words, if $CV(s_i) = x$ then $\mu_{s_i}(x) = 1$.

These 3 conditions are necessary and sufficient for the transformations between $\vartheta \in [0, 1]$ values and linguistic 2-tuples without any loss of information. The membership degree of the linguistic term $i$, expressed as $\mu_{s_i}$, is defined as:

$$\mu_{s_i}(\vartheta) = \begin{cases} 0, & if \ \vartheta \le a_i \ or \ \vartheta \ge c_i \\ \dfrac{\vartheta - a_i}{b_i - a_i}, & if \ \vartheta \le b_i \\ \dfrac{c_i - \vartheta}{c_i - b_i}, & if \ \vartheta > b_i \end{cases} \tag{8}$$

The linguistic 2-tuple enables the use of different aggregation operators. In this paper, we use the weighted average operator proposed by Herrera and Martinez (2000a) due to its simplicity and compatibility with the use of different criteria weights determined by AHP. The weighted average allows the combination of multiple criteria $x_i | i \in \{1, 2, 3, \ldots, n\}$, each of which with a different weight to determine the value $\bar{x}$.

Let $x = \{(r_1, \alpha_1), \cdots (r_n, \alpha_n)\}$ be a set of 2-tuples and $\{\beta_1, \cdots, \beta_n\}$ be its continuous representation. For a weighting vector $w = \{w_1, \cdots w_n\}$, where $0 \le w_i \le 1$ and $\sum_{i=1}^{n} w_i = 1$, the 2-tuple weighted average $\bar{x}$ is:

$$\bar{x} = \Delta\left(\sum_{i=1}^{n} w_i \cdot \beta_i\right) \tag{9}$$

## 5. Proposed model for supplier assessment

The proposed method is divided in four steps, as shown in Fig. 2. In summary, after determining which criteria will be used to evaluate suppliers, AHP is used in Step 1 to determine their relative weights. Later on, quantitative data are collected and experts' judgements are carried out in Step 2 to feed into 2-tuple and calculate the final assessment of each supplier. Rezaei and Ortt's (2012) segmentation matrix is used in Step 3 to classify suppliers. Finally, in Step 4 decision makers analyze results and devise practical implications to improve supply base management.

The first step of the method involves the selection of which criteria should be adopted by the company to measure each of the two dimensions – supplier capabilities and willingness to cooperate. Tables 1 and 2 present criteria that managers can include in each dimension. This task should be carried out by purchasing managers, who are also in charge of carrying out pairwise comparisons of all the criteria and apply AHP calculations to determine their relative importance for the company. Let $m$ and $n$ be the number criteria in each dimension. Then, purchasing experts need to create two comparison matrices as show in Eq. (1), with dimensions $m \times m$ and $n \times n$, using the evaluation criteria in Table 3. Later on, the relative weights of the criteria in both dimensions are calculated using the geometric mean method with Eq. (2). Consistency of both matrices are then checked using the consistency ratio, as described by Eqs. (3)–(5).

In Step 2, suppliers are evaluated against the criteria chosen in the previous step, which can be done in two ways. The first is by having purchasing experts judging the suppliers qualitatively, whereas the second is by using historical performance data. Fuzzy 2-tuple linguistic representation (Herrera & Martinez, 2000a, b) was deemed appropriate for this step given its ability to work concurrently with quantitative and qualitative variables in aggregation operations. The three conditions necessary to convert between linguistic terms and quantitative values normalized to a 0 to 1 scale, as discussed in Section 4, need to be satisfied. The linguistic set $S$ used to evaluate suppliers has seven terms: Nothing (N), Very Low (VL), Low (L), Medium (M), High (H), Very High (VH) and Perfect (P). Hence the set $S$ can be expressed as:

$$S = \{s_0 : Nothing, \ s_1 : Very\ Low, \ s_2 : Low, \ s_3 : Medium, \\ s_4 : High, \ s_5 : Very\ High, \ s_6 : Perfect\} \tag{10}$$

Fig. 3 illustrates the membership functions of each term in the linguistic set. The set $S$ should be used to aggregate criteria in both dimensions.

The judgments by purchasing managers are used to determine the values for qualitative criteria using the linguistic terms in set $S$. The conversion to the continuous representation $\beta$ is done with Eq. (7). Historical data can be used to determine the performance of quantitative criteria, which need to be normalized to $\vartheta \in [0, 1]$ in order to enable 2-tuple representation. The conversion of normalized values to fuzzy 2-tuple representation is done by Eq. (8).

In Step 3, results from the evaluation of all suppliers in Step 2 are used to segment the supplier base by aggregating their performance in a two-dimension chart. The weights determined in Step 1 for each criterion can be combined with the evaluations in a continuous representation $\beta$ to calculate the score of all suppliers in both dimensions using the weighted average method described by Eq. (9). The continuous representation of the evaluations of each supplier can be converted into 2-tuples using Eq. (7). The segment with lowest performance includes the terms N and VL, with $\beta \in [0, 1.5)$. The intermediary segment encompasses the terms L, M and H, with $\beta \in [1.5, 4.5)$ and the segment with superior performance includes the terms VH and P, with $\beta \in [4.5, 6.0]$.

Finally, in Step 4, purchasing managers need to make decisions based on the chart built in Step 3 that depicts the supply

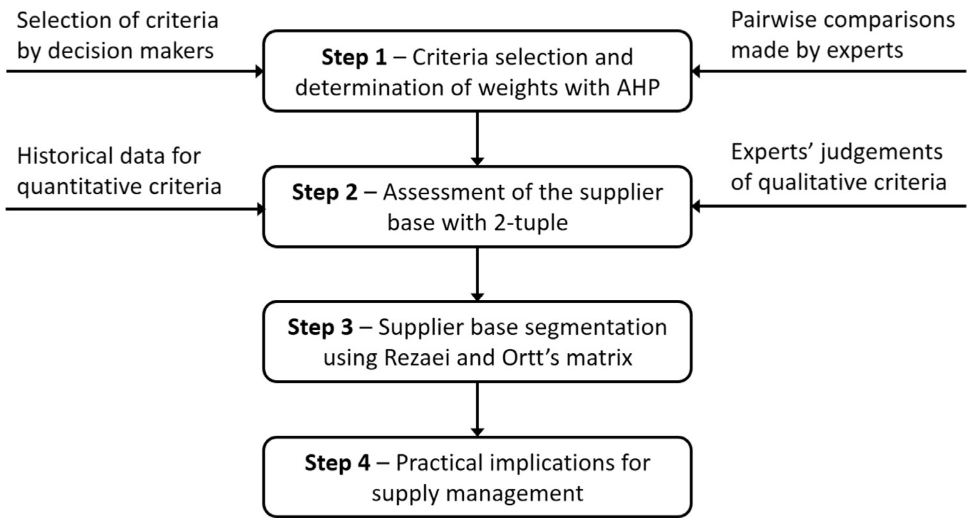


**Fig. 2.** Steps of the proposed model.

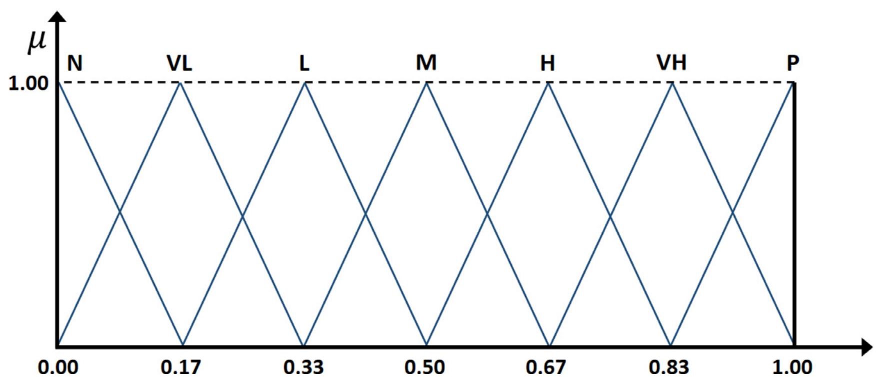


**Fig. 3.** Membership functions of the terms in the linguistic set *S*.

base segmentation according to their performance. The segmented management of the supply base enables the company to set priorities and better allocate resources to suppliers. Depending on which segment a supplier falls into, the buyer firms can make decisions such as invest in supplier improvement programs or even replace suppliers in cases of repeatedly low performance results. Osiro et al. (2014) and Rezaei et al. (2015) provide guidelines to link segmented assessment to supplier development initiatives. Wagner (2006) and Dalvi and Kant (2015) also discuss practices and benefits associated with the management and development of the supply base. The effectiveness of the decisions made in this step depends upon the ability of the company to mix the results in the segmentation chart and the expertise of purchasing managers to determine how the guidelines presented by these authors should be enacted.

### 5.1. Illustrative application case

In order to illustrate the proposed method, a practical application was carried out in the pharmaceutical supply center (PSC) of a public teaching hospital in Brazil. A company from the service sector was chosen because most of the applications of portfolio models take place in industrial settings. The PSC is the department in charge of supplying all pharmaceutical drugs demanded by the hospital. Other two sectors of the hospital participated during this application: the pharmacy department and the purchasing department.

During Step 1, the choice and weighting of criteria occurred in meetings involving representatives from all the participating departments. In these meetings, Tables 1 and 2 assisted participants in selecting which criteria should be added to the dimensions (i) supplier capabilities and (ii) willingness to cooperate. As shown in Table 5, six criteria were chosen for each dimension. Among all criteria, 2 were quantitative and 10 were qualitative. The two quantitative criteria were delivery lead time ($C_3$) and delivery reliability ($C_6$). It is worth noting that the participants did not deem the cost of the supplied products to be relevant in this application because the legislation of the bidding process in Brazilian public hospitals requires the choice of suppliers with the lowest price.

After choosing the criteria, a meeting was held with representatives of all departments to conduct pairwise comparisons and build the AHP matrices for the two dimensions. The meeting enabled participants to reach a better understanding and consensus over the relative importance of each criterion. The researchers assisted the participants in building consistent comparison matrices, with consistency ratios below 0.1. Tables 6 and 7 present the pairwise evaluations, criteria weights and consistency ratios in both dimensions.

In Step 2, a sample with 12 suppliers was used to demonstrate how the evaluations and calculations should be performed. Quantitative criteria were evaluated using historical data. The scores for delivery lead time were calculated using the median of the delivery time normalized to a $[0, 1]$ interval. Suppliers with median delivery time below 10 days were considered to be high performing

**Table 5**
Criteria selected for each dimension.

| Supplier capabilities | | Willingness to cooperate | |
|---|---|---|---|
| $C_1$ | Product quality | $C_7$ | Openness to frequent and honest communication |
| $C_2$ | Packaging capabilities | $C_8$ | Transparency |
| $C_3$ | Delivery lead time | $C_9$ | Ethics, mutual respect and honesty |
| $C_4$ | Post-sales support | $C_{10}$ | Previous experience with the supplier |
| $C_5$ | Billing and order processing system | $C_{11}$ | Compliance with the bidding legislation |
| $C_6$ | Delivery reliability | $C_{12}$ | Commitment to quality |

**Table 6**
Pairwise comparisons and weights of the *supplier capabilities* dimension.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | Weight |
|---|---|---|---|---|---|---|---|
| **$C_1$** | 1.000 | 4.000 | 0.333 | 4.000 | 7.000 | 0.250 | 0.1707 |
| **$C_2$** | 0.250 | 1.000 | 0.200 | 2.000 | 5.000 | 0.333 | 0.0873 |
| **$C_3$** | 3.000 | 5.000 | 1.000 | 6.000 | 7.000 | 1.000 | 0.3445 |
| **$C_4$** | 0.250 | 0.500 | 0.167 | 1.000 | 3.000 | 0.250 | 0.0588 |
| **$C_5$** | 0.143 | 0.200 | 0.143 | 0.333 | 1.000 | 0.143 | 0.0283 |
| **$C_6$** | 4.000 | 3.000 | 1.000 | 4.000 | 7.000 | 1.000 | 0.3103 |
| | | | | | | **CR** | **0.0707** |

**Table 7**
Pairwise comparisons and weights of the *willingness to cooperate* dimension.

| | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{11}$ | $C_{12}$ | Weight |
|---|---|---|---|---|---|---|---|
| **$C_7$** | 1.000 | 5.000 | 4.000 | 3.000 | 6.000 | 2.000 | 0.3781 |
| **$C_8$** | 0.200 | 1.000 | 0.333 | 0.333 | 3.000 | 0.250 | 0.0638 |
| **$C_9$** | 0.250 | 3.000 | 1.000 | 0.500 | 5.000 | 0.333 | 0.1168 |
| **$C_{10}$** | 0.333 | 3.000 | 2.000 | 1.000 | 5.000 | 2.000 | 0.2081 |
| **$C_{11}$** | 0.167 | 0.333 | 0.200 | 0.200 | 1.000 | 0.200 | 0.0349 |
| **$C_{12}$** | 0.500 | 4.000 | 3.000 | 0.500 | 5.000 | 1.000 | 0.1983 |
| | | | | | | **CR** | **0.0605** |

**Table 8**
Calculation of scores for delivery lead time.

| Supplier | Median delivery lead time in days | Normalized score |
|---|---|---|
| $S_1$ | 16 | 0.8000 |
| $S_2$ | 20.5 | 0.6500 |
| $S_3$ | 10 | 1.0000 |
| $S_4$ | 27 | 0.4333 |
| $S_5$ | 16 | 0.8000 |
| $S_6$ | 26 | 0.4667 |
| $S_7$ | 10 | 1.0000 |
| $S_8$ | 92 | 0.0000 |
| $S_9$ | 23 | 0.5667 |
| $S_{10}$ | 29.5 | 0.3500 |
| $S_{11}$ | 40 | 0.0000 |
| $S_{12}$ | 41.5 | 0.0000 |

and received score 1, whereas suppliers with median lead times equal or greater than 40 days scored 0. Table 8 shows the scores for all 12 suppliers.

The scores of the second quantitative criteria – delivery reliability – were calculated as the weighted average of four sub criteria: (i) complete deliveries, (ii) score of orders canceled, (iii) notifications of orders with errors and (iv) variability in delivery time. Complete deliveries were measured as the ratio between orders delivered with all purchased items and the total number of orders issued to the supplier. The score for orders canceled was measured in a $[0,1]$ scale where suppliers with 4 or more orders canceled scored 0 and suppliers with no orders canceled scored 1. The score for the third sub criteria was calculated in a similar manner, thus assigning score 0 to suppliers with 4 or more notifications of errors in their orders. Finally, the evaluation of the variability in delivery time was done using the coefficient of variation of the delivery time. The weights of these 4 sub criteria were determined with pairwise comparisons and AHP's geometric mean method. Table 9 presents the pairwise comparisons and calculation of weights, along with the resulting consistency ratio.

Table 10 shows the scores received by each of the 12 suppliers for the 4 sub criteria related to delivery reliability. The scores were normalized into a $[0,1]$ interval. Thus, the final scores for criteria $C_6$ were calculated by summing up the multiplications of the scores in each sub criteria and their respective weights.

The qualitative criteria were evaluated using the seven linguistic terms in Fig. 3. The PSC team was responsible for evaluating criteria $C_4$, $C_5$, $C_7$, $C_8$, $C_9$, $C_{10}$, $C_{11}$ and $C_{12}$. The staff in the pharmacy department, who are responsible for receiving orders from suppliers, evaluated criteria $C_1$, $C_2$, $C_5$ and $C_{10}$. The purchasing department team, which comprises purchasing assistants and criers, was in charge of criteria $C_7$, $C_8$, $C_9$, $C_{10}$ and $C_{11}$. The evaluations assigned to each supplier by the three departments are shown in Tables 11, 12 and 13, respectively.

Tables 14 and 15 show the fuzzy 2-tuple representation of the evaluations assigned to each supplier in all criteria of the dimensions (i) supplier capabilities and (ii) willingness to cooperate, respectively. The 2-tuple linguistic representation of the quantitative criteria $C_3$ and $C_6$ associated with the value $\vartheta \in [0, 1]$ was determined using Eq. (8). The qualitative criteria $C_1$, $C_2$, $C_4$, $C_{11}$ and $C_{12}$ were evaluated by only one department and had their linguistic evaluations copied directly to Tables 14 and 15. The determination of the final evaluation of criteria submitted to more than one department was done using the weighted average method described in Eq. (9) using equal weights for each department.

In Step 3 the 2-tuples in Tables 14 and 15 were converted into the continuous representation $\beta$ using Eq. (7) to segment the supply base. The determination of the final score for each supplier was obtained as the weighted average of the scores received in each criteria, which is calculated using Eq. (9). The linguistic term associated with the 2-tuple representation of the final score $\beta$ is determined using Eq. (7). Tables 16 and 17 present the results for the two dimensions.

Fig. 4 presents the segmentation of the 12 suppliers based on the results from Tables 16 and 17. The segmentation is done by dividing each axis in three parts according to the linguistic terms adopted. The low performing segment includes terms N and VL, the intermediary segment includes the terms L, M and H and the high performing segment comprises the terms VH and P.

The segmentation revealed problems with the low performance of suppliers $S_8$, $S_{11}$ and $S_{12}$, which were shared with decision makers during Step 4. As a consequence, improvement actions were initiated to track closely the contracts the hospital already had with these suppliers. On the other hand, Supplier $S_3$ was found to be the best performing supplier and was considered as a reference for future purchases, as well as for initiatives to improve low performing suppliers.

## 6. Results and discussions

The application of the proposed model enabled the analysis of the supply base of pharmaceutical drugs of a public teach-

**Table 9**
Determination of weights of the sub criteria related to delivery reliability.

| | Complete deliveries | Orders canceled | Order errors | Variability | Weight |
|---|---|---|---|---|---|
| **Complete deliveries** | 1.000 | 3.000 | 3.000 | 0.500 | 0.2967 |
| **Orders canceled** | 0.333 | 1.000 | 1.000 | 0.250 | 0.1094 |
| **Order errors** | 0.333 | 1.000 | 1.000 | 0.250 | 0.1094 |
| **Variability** | 2.000 | 4.000 | 4.000 | 1.000 | 0.4845 |
| **CR** | | | | | **0.0076** |

**Table 10**
Calculation of the final score for delivery reliability.

| Supplier | Complete deliveries | Orders canceled | Order errors | Delivery time variability | Delivery reliability |
|---|---|---|---|---|---|
| $S_1$ | 0.8438 | 1.0000 | 0.5000 | 0.6402 | 0.7246 |
| $S_2$ | 0.8333 | 1.0000 | 0.7500 | 0.4665 | 0.6648 |
| $S_3$ | 0.7941 | 1.0000 | 1.0000 | 0.8156 | 0.8496 |
| $S_4$ | 0.5833 | 1.0000 | 0.7500 | 0.0000 | 0.3646 |
| $S_5$ | 0.7174 | 1.0000 | 0.2500 | 0.6935 | 0.6856 |
| $S_6$ | 0.7193 | 0.5000 | 1.0000 | 0.1776 | 0.4636 |
| $S_7$ | 0.9231 | 1.0000 | 1.0000 | 0.6499 | 0.8076 |
| $S_8$ | 0.0909 | 0.0000 | 0.5000 | 0.0000 | 0.0817 |
| $S_9$ | 0.9048 | 1.0000 | 0.7500 | 0.6935 | 0.7959 |
| $S_{10}$ | 0.4048 | 0.0000 | 0.2500 | 0.0000 | 0.1474 |
| $S_{11}$ | 0.6667 | 1.0000 | 0.7500 | 0.1530 | 0.4634 |
| $S_{12}$ | 0.3333 | 0.5000 | 0.0000 | 0.0000 | 0.1536 |

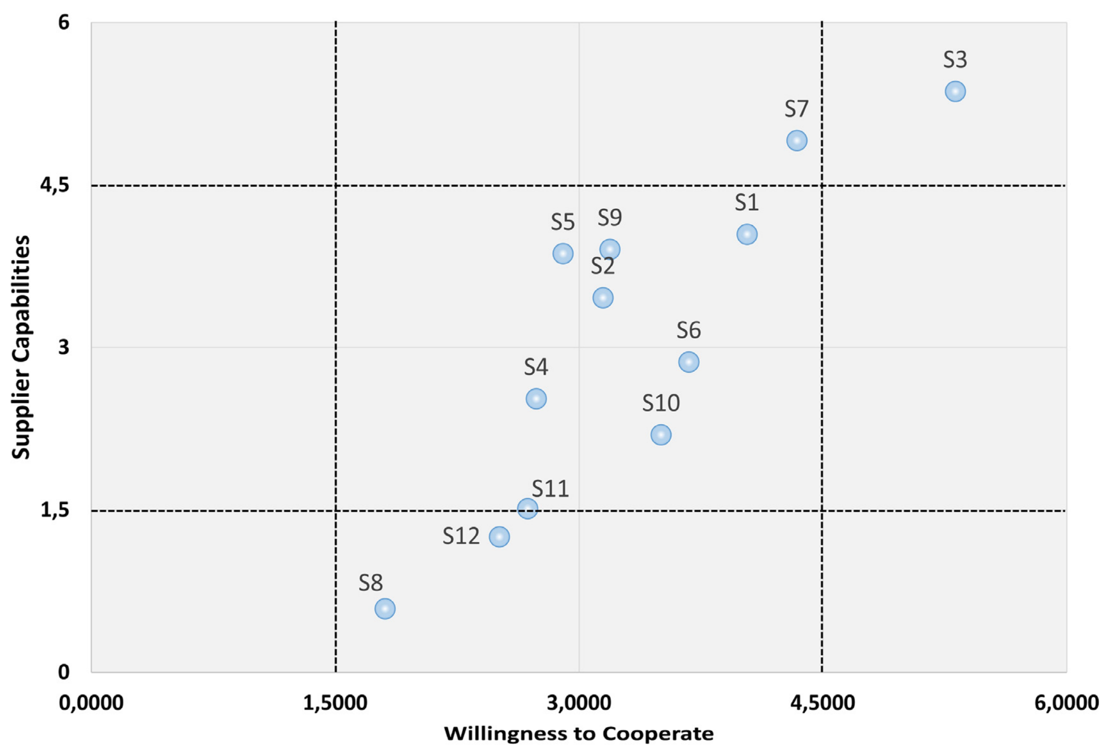


**Fig. 4.** Segmentation of the supply base.

ing hospital, which contributed improving decision making in a company from the service sector. This facilitated the work of supply managers in more effectively tracking supplier performance and order processing, especially for low performing suppliers. According to the views of purchasing managers at the hospital, the supply base portfolio may impact positively on the quality of the products purchased, as well as the service level of suppliers with respect to compliance with specifications, product availability and order oversizing.

Participants experienced little difficulty throughout the application of the proposed model. A significant amount of time was spent with selecting criteria and carrying out pairwise comparisons to calculate the relative importance of criteria in each performance dimension. Consistent matrices were not obtained at first, which required some additional discussions and modifications with the aid of the researchers. Ultimately, participants agreed upon consistent matrices for both dimensions.

During the evaluation of suppliers, the use of linguistic terms made it easier for decision makers to judge suppliers against qualitative criteria, because such terms are used in their daily routine. If AHP had been used to compare every pair of suppliers for all criteria, the total amount of pairwise comparisons would have made this task too difficult and cumbersome. Besides, any change in the supply base would require a new round of pairwise comparisons to

**Table 11**
Qualitative evaluations made by the PSC team.

| | $C_4$ | $C_5$ | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{12}$ |
|---|---|---|---|---|---|---|---|
| $S_1$ | H | H | L | H | H | H | H |
| $S_2$ | VL | VL | L | L | H | M | L |
| $S_3$ | VH | VH | VH | VH | VH | VH | VH |
| $S_4$ | L | L | L | M | M | L | L |
| $S_5$ | VL | M | VL | L | L | L | VL |
| $S_6$ | M | H | H | M | M | M | H |
| $S_7$ | M | VH | VH | H | H | H | H |
| $S_8$ | VL | VL | VL | VL | VL | VL | VL |
| $S_9$ | L | M | M | M | M | M | M |
| $S_{10}$ | M | M | H | H | H | H | H |
| $S_{11}$ | VL | L | L | VL | L | L | L |
| $S_{12}$ | VL | VL | VL | VL | L | L | L |

**Table 12**
Qualitative evaluations made by the pharmacy staff.

| | $C_1$ | $C_2$ | $C_5$ | $C_{10}$ |
|---|---|---|---|---|
| $S_1$ | L | H | H | M |
| $S_2$ | M | M | L | L |
| $S_3$ | VH | VH | H | VH |
| $S_4$ | M | M | L | M |
| $S_5$ | M | M | H | M |
| $S_6$ | M | M | L | M |
| $S_7$ | H | H | H | H |
| $S_8$ | VL | L | VL | VL |
| $S_9$ | H | H | H | H |
| $S_{10}$ | H | M | L | L |
| $S_{11}$ | L | L | M | M |
| $S_{12}$ | M | H | L | L |

**Table 13**
Qualitative evaluations made by the purchasing department.

| | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{11}$ |
|---|---|---|---|---|---|
| $S_1$ | VH | VH | P | H | H |
| $S_2$ | H | VH | H | VH | H |
| $S_3$ | P | VH | P | VH | P |
| $S_4$ | H | H | M | H | H |
| $S_5$ | VH | VH | VH | VH | H |
| $S_6$ | H | VH | H | H | H |
| $S_7$ | H | VH | H | H | P |
| $S_8$ | H | VH | L | H | H |
| $S_9$ | M | M | M | VH | H |
| $S_{10}$ | H | VH | M | VH | N |
| $S_{11}$ | VH | H | M | H | H |
| $S_{12}$ | M | VH | H | H | H |

**Table 14**
Linguistic 2-tuples of the partial evaluations of suppliers in the *supplier capabilities* dimension.

| | $C_1$ | | $C_2$ | | $C_3$ | | $C_4$ | | $C_5$ | | $C_6$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ |
| $S_1$ | L | 0 | H | 0 | VH | −0.2 | H | 0 | H | 0 | H | 0.348 |
| $S_2$ | M | 0 | M | 0 | H | −0.1 | VL | 0 | L | −0.5 | H | −0.011 |
| $S_3$ | VH | 0 | VH | 0 | P | 0 | VH | 0 | VH | −0.5 | VH | 0.097 |
| $S_4$ | M | 0 | M | 0 | M | −0.4 | L | 0 | L | 0 | L | 0.187 |
| $S_5$ | M | 0 | M | 0 | VH | −0.2 | VL | 0 | H | −0.5 | H | 0.114 |
| $S_6$ | M | 0 | M | 0 | M | −0.2 | M | 0 | M | 0 | M | −0.219 |
| $S_7$ | H | 0 | H | 0 | P | 0 | M | 0 | VH | −0.5 | VH | −0.155 |
| $S_8$ | VL | 0 | L | 0 | N | 0 | VL | 0 | VL | 0 | N | 0.490 |
| $S_9$ | H | 0 | H | 0 | M | 0.4 | L | 0 | H | −0.5 | VH | −0.225 |
| $S_{10}$ | H | 0 | M | 0 | L | 0.1 | M | 0 | M | −0.5 | VL | −0.115 |
| $S_{11}$ | L | 0 | L | 0 | N | 0 | VL | 0 | M | −0.5 | M | −0.219 |
| $S_{12}$ | M | 0 | H | 0 | N | 0 | VL | 0 | L | −0.5 | VL | −0.078 |

**Table 15**
Linguistic 2-tuples of the partial evaluations of suppliers in the *willingness to cooperate* dimension.

| | $C_7$ | | $C_8$ | | $C_9$ | | $C_{10}$ | | $C_{11}$ | | $C_{12}$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ | $s$ | $\alpha$ |
| $S_1$ | H | 0 | H | 0 | H | 0 | H | 0 | VH | 0 | H | 0 |
| $S_2$ | M | 0 | H | −0.5 | H | 0 | M | −0.33 | VH | 0 | M | 0 |
| $S_3$ | P | −0.5 | VH | 0 | P | -0.5 | VH | 0.33 | VH | 0 | VH | 0 |
| $S_4$ | M | −0.5 | H | −0.5 | H | −0.5 | M | 0 | H | 0 | L | 0 |
| $S_5$ | M | 0 | H | −0.5 | M | 0 | M | 0 | VH | 0 | L | 0 |
| $S_6$ | H | 0 | H | −0.5 | H | −0.5 | H | −0.33 | VH | 0 | M | 0 |
| $S_7$ | VH | −0.5 | H | 0 | VH | 0 | H | 0 | VH | 0 | H | 0 |
| $S_8$ | L | −0.5 | M | −0.5 | M | −0.5 | L | 0 | VH | 0 | VL | 0 |
| $S_9$ | M | 0 | H | 0 | H | −0.5 | M | 0.33 | M | 0 | M | 0 |
| $S_{10}$ | H | −0.5 | VH | −0.5 | L | 0 | M | 0.33 | VH | 0 | H | 0 |
| $S_{11}$ | M | −0.5 | M | −0.5 | M | 0 | M | 0.33 | H | 0 | L | 0 |
| $S_{12}$ | M | −0.5 | M | −0.5 | M | 0 | L | 0.33 | VH | 0 | L | 0 |

determine the scores of all suppliers, thus slowing down the whole process.

Participants showed no difficulty in understanding the seven terms included in the linguistic set $S$. It is worth noting, however, that in future applications decision makers can modify the set of terms that are used to describe the two dimensions to adjust the model to their own purchasing strategies.

The aggregation of quantitative data extracted from historical records with qualitative data based on the judgements of experts allowed for a comprehensive evaluation of suppliers in both dimensions. The simplicity of the 2-tuple representation facilitated the understanding of how quantitative and qualitative criteria contributed to each supplier's overall evaluation.

The segmentation of the supply base using Rezaei and Ortt's (2012) dimensions allowed managers to focus their actions on aspects directly linked with the management of relationships with suppliers. The final result of the model, shown in Fig. 4, enabled a shared view of the supplier base segmentation and evaluation among all participants. Prior to this application, purchasing managers already knew that some suppliers had low delivery performance and lacked willingness to cooperate. With the proposed model, decision makers now have objective measurements of how each supplier performs in these dimensions, making it possible to take more effective actions.

For example, suppliers $S_8$, $S_{11}$ and $S_{12}$ need to improve their performance in both dimensions – supplier capabilities and willingness to cooperate, as shown in Fig. 4. After a thorough analysis of Table 16, the purchasing team noticed that these suppliers showed poor performance with respect to delivery lead time (criteria $C_3$), which has the highest weight factor (0.345) in the dimension supplier capabilities (see Table 6). These three suppliers also had the lowest overall scores for the dimension willingness to cooperate. As shown in Table 17, these low scores are a consequence of poor performance in openness to frequent and honest communication ($C_7$), that is the criteria with the highest weight in this dimension (0.378 – see Table 7). Based on this information, the purchasing team is now planning improvement initiatives to reduce delivery lead time and enhance communication with suppliers $S_8$, $S_{11}$ and $S_{12}$. The proposed methodology can be used by the purchasing team to track the performance of these suppliers as the improvement initiatives unfold to verify their effectiveness.

The purchasing department already had a database with historical data for quantitative measures as compete deliveries, orders canceled and order errors. However, before this research took place, there was not a systematic method to analyze performance data and identify deficiencies, improvement priorities and keep track of supplier performance. Hence, the aggregation of historical quantitative data with qualitative judgements made it possible for

**Table 16**
Partial and final evaluations for the dimension *supplier capabilities*.

| Criteria | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | Final score ($\beta$) | 2-Tuple representation | |
|---|---|---|---|---|---|---|---|---|---|
| Weights | 0.171 | 0.087 | 0.345 | 0.059 | 0.028 | 0.310 | | $s$ | $\alpha$ |
| $S_1$ | 2.00 | 4.00 | 4.80 | 4.00 | 4.00 | 4.35 | 4.0420 | H | 0.04 |
| $S_2$ | 3.00 | 3.00 | 3.90 | 1.00 | 1.50 | 3.99 | 3.4566 | M | 0.46 |
| $S_3$ | 5.00 | 5.00 | 6.00 | 5.00 | 4.50 | 5.10 | 5.3606 | VH | 0.36 |
| $S_4$ | 3.00 | 3.00 | 2.60 | 2.00 | 2.00 | 2.19 | 2.5229 | M | −0.48 |
| $S_5$ | 3.00 | 3.00 | 4.80 | 1.00 | 3.50 | 4.11 | 3.8621 | H | −0.14 |
| $S_6$ | 3.00 | 3.00 | 2.80 | 3.00 | 3.00 | 2.78 | 2.8633 | M | −0.14 |
| $S_7$ | 4.00 | 4.00 | 6.00 | 3.00 | 4.50 | 4.85 | 4.9067 | VH | −0.09 |
| $S_8$ | 1.00 | 2.00 | 0.00 | 1.00 | 1.00 | 0.49 | 0.5846 | VL | −0.42 |
| $S_9$ | 4.00 | 4.00 | 3.40 | 2.00 | 3.50 | 4.78 | 3.9020 | H | −0.10 |
| $S_{10}$ | 4.00 | 3.00 | 2.10 | 3.00 | 2.50 | 0.88 | 2.1902 | L | 0.19 |
| $S_{11}$ | 2.00 | 2.00 | 0.00 | 1.00 | 2.50 | 2.78 | 1.5085 | L | −0.49 |
| $S_{12}$ | 3.00 | 4.00 | 0.00 | 1.00 | 1.50 | 0.92 | 1.2487 | VL | 0.25 |

**Table 17**
Partial and final evaluations for the dimension *willingness to cooperate*.

| Criteria | $C_7$ | $C_8$ | $C_9$ | $C_{10}$ | $C_{11}$ | $C_{12}$ | Final score ($\beta$) | 2-Tuple representation | |
|---|---|---|---|---|---|---|---|---|---|
| Weights | 0.378 | 0.064 | 0.117 | 0.208 | 0.035 | 0.198 | | $s$ | $\alpha$ |
| $S_1$ | 4.00 | 4.00 | 4.00 | 4.00 | 5.00 | 4.00 | 4,0349 | H | 0,03 |
| $S_2$ | 3.00 | 3.50 | 4.00 | 2.67 | 5.00 | 3.00 | 3,1491 | M | 0,15 |
| $S_3$ | 5.50 | 5.00 | 5.50 | 5.33 | 5.00 | 5.00 | 5,3168 | VH | 0,32 |
| $S_4$ | 2.50 | 3.50 | 3.50 | 3.00 | 4.00 | 2.00 | 2,7379 | M | −0,26 |
| $S_5$ | 3.00 | 3.50 | 3.00 | 3.00 | 5.00 | 2.00 | 2,9034 | M | −−0,10 |
| $S_6$ | 4.00 | 3.50 | 3.50 | 3.67 | 5.00 | 3.00 | 3,6769 | H | −0,32 |
| $S_7$ | 4.50 | 4.00 | 5.00 | 4.00 | 5.00 | 4.00 | 4,3408 | H | 0,34 |
| $S_8$ | 1.50 | 2.50 | 2.50 | 2.00 | 5.00 | 1.00 | 1,8077 | L | −0,19 |
| $S_9$ | 3.00 | 4.00 | 3.50 | 3.33 | 3.00 | 3.00 | 3,1916 | M | 0,19 |
| $S_{10}$ | 3.50 | 4.50 | 2.00 | 3.33 | 5.00 | 4.00 | 3,5054 | H | −0,49 |
| $S_{11}$ | 2.50 | 2.50 | 3.00 | 3.33 | 4.00 | 2.00 | 2,6850 | M | −0,31 |
| $S_{12}$ | 2.50 | 2.50 | 3.00 | 2.33 | 5.00 | 2.00 | 2,5118 | M | −0,49 |

all the actors involved to share priorities and reach consensus with respect to the performance of suppliers. The application of the proposed method showed that storing performance data has little use if there is not a system in place to support decision making.

## 7. Conclusion

The segmentation of the supply base is an important activity in the supply management process. Researchers and practitioners have advocated the adoption of portfolio models for supply base segmentation. Such models would allow organizations to use different strategies focusing each segment of suppliers. Unlike the majority of the work addressing purchasing portfolio models found in the literature, which segment the supply base according to the characteristics of the purchased item, the method proposed in this paper classifies suppliers using the dimensions suggested by Rezaei and Ortt (2012), which emphasize characteristics of the relationship with suppliers. By focusing on the relationship, purchasing managers may take actions that address the specific issues of each supplier.

There are a number of approaches in the literature that employ MCDM techniques to aggregate multiple criteria related to supplier capabilities and willingness to cooperate. Such approaches aggregate qualitative criteria based on the judgements of experts to determine the performance of suppliers in each dimension. However, some practical applications would benefit from the adoption of quantitative criteria obtained from historical data. The model herein proposed addresses this gap by using fuzzy 2-tuple to aggregate qualitative and quantitative criteria to assess suppliers in both dimensions. This enables not only a more comprehensive evaluation of the supply base, but also the formulation of more flexible models by combining quantitative a qualitative data without any loss of information.

Unlike fuzzy inference systems (FIS), aggregation operations with 2-tuple representation do not require a rule base. If a FIS had been used in the application reported in Section 5.1, the aggregation of the six variables and seven linguistic terms in one of the dimensions would require a base with $7^6 = 117,649$ rules, which would make the study impracticable. The 2-tuple linguistic representation allowed the aggregation operations to be performed in a continuous domain of $\beta$ values. In contrast with other CWW techniques that model problems in discrete domains, the proposed method is capable of aggregating multiple quantitative and qualitative criteria without any loss of information.

The results of the illustrative application show that the use of AHP to weigh the criteria along with the fuzzy 2-tuple representation to aggregate variables is a promising alternative to segment the supply base focusing on relationship aspects. In this sense, this paper contributes to the ongoing debate on purchasing portfolio models by proposing a simpler and more efficient approach to aggregate quantitative and qualitative criteria to evaluate and segment suppliers. Finally, the application of this model in a teaching hospital indicates that the service sector may also benefit from purchasing portfolio models.

In spite of all the advantages of the method proposed in this paper, there are some shortcomings that need to be pointed out. First, because the method uses AHP, the set of criteria should not change very often. If the company choses to modify the criteria, a new pairwise comparison matrix would be needed, which could significantly change the weights used. Secondly, the set of criteria in each dimension needs to be limited to a number not greater than 8, otherwise it would become too difficult to reach a consistent comparison matrix. Another weakness is that even though fuzzy 2-tuple is simpler and more flexible, it does not model knowledge as effectively as Fuzzy Inference Systems (FIS). We chose 2-tuple over FIS because the latter would make the method too complex, due to the number of rules that would be necessary. Finally, recent literature has used a method known as hesitant fuzzy Linguistic term set (HFLTS) for qualitative judgements, that allow experts to use more complex linguistic expressions (Rodriguez, Martinez, & Herrera, 2012). Our approach still relies on traditional fuzzy linguistic representation, but future research should study how HFLTS can be integrated with quantitative criteria.

In addition to the shortcomings listed previously, we believe that future research should also address some practical aspects of the proposed method. First, more applications need to be carried out in companies with product development processes that require a more intense relationship between the buyer firm and its suppliers. This would probably lead to quantitative criteria being added to the willingness to cooperate dimension, which in the PSC application reported in this paper consisted only of qualitative criteria. Furthermore, different strategic approaches that prioritize certain performance measures and relationship criteria, such as lean and agile manufacturing, should be addressed in future research because they might demand adaptations such as the differentiation of compensatory and non-compensatory criteria. Another prominent strain of research is the combination of traditional criteria with environmental and social aspects in the supplier evaluation process (Govindan et al., 2015). Hence, future research should discuss how to integrate such dimensions to Rezaei and Ortt's (2012) matrix and stimulate suppliers to improve their environmental performance.

## Acknowledgments

This work was supported by CNPq (Brazil's National Council for Scientific and Technological Development) [grant number 445190/2014–0]; and Fapemig (Minas Gerais State Science Foundation) [grant number APQ-00422-14].

## References

Abdollahi, M., Arvan, M., & Razmi, J. (2015). An integrated approach for supplier portfolio selection: Lean or agile? *Expert Systems with Applications, 42*(1), 679–690. https://doi.org/10.1016/j.eswa.2014.08.019.

Aydın Keskin, G., İlhan, S., & Özkan, C. (2010). The Fuzzy ART algorithm: A categorization method for supplier evaluation and selection. *Expert Systems with Applications, 37*(2), 1235–1240. http://doi.org/10.1016/j.eswa.2009.06.004.

Bensaou, M. (1999). Portfolios of buyer-supplier relationships. *Sloan Management Review, 40*(4), 35–44.

Brunelli, M. (2015). *Introduction to the Analytic Hierarchy Process* Available at *http://dx.doi.org/10.1007/978-3-319-12502-2*.

Caniels, M. C. J., & Gelderman, C. J. (2007). Power and interdependence in buyer supplier relationships: A purchasing portfolio approach. *Industrial Marketing Management, 36*(2), 219–229. http://doi.org/10.1016/j.indmarman.2005.08.012.

Chai, J., Liu, J. N. K., & Ngai, E. W. T. (2013). Application of decision-making techniques in supplier selection: A systematic review of literature. *Expert Systems with Applications, 40*(10), 3872–3885. http://doi.org/10.1016/j.eswa.2012.12.040.

Cid-López, A., Hornos, M. J., Carrasco, R. A., & Herrera-Viedma, E. (2016). Applying a linguistic multi-criteria decision-making model to the analysis of ICT suppliers' offers. *Expert Systems With Applications, 57*, 127–138. http://dx.doi.org/10.1016/j.eswa.2016.03.025.

Crawford, G. B. (1987). The geometric mean procedure for estimating the scale of a judgment matrix. *Mathematical Modelling, 9*(3-5), 327–334. http://doi.org/10.1016/0270-0255(87)90489-1.

Dalvi, M. V., & Kant, R. (2015). Benefits, criteria and activities of supplier development: A categorical literature review. *Asia Pacific Journal of Marketing and Logistics, 27*(4), 653–675. http://doi.org/10.1108/APJML-11-2014-0161.

Day, M., Magnan, G. M., & Munkgaard, M. (2010). Evaluating the bases of supplier segmentation : A review and taxonomy. *Industrial Marketing Management, 39*(4), 625–639. http://doi.org/10.1016/j.indmarman.2009.06.001.

Dempsey, W. A. (1978). Vendor selection and the buying process. *Industrial Marketing Management, 7*(4), 257–267. http://doi.org/10.1016/0019-8501(78)90044-5.

Dickson, G. W. (1966). An analysis of supplier selection systems and decisions. *Journal of Purchasing, 2*(1), 5–17.

Drake, P. R., Lee, D. M., & Hussain, M. (2013). The lean and agile purchasing portfolio model. *Supply Chain Management: An International Journal, 8*(1), 3–20. http://doi.org/10.1108/13598541311293140.

Dubois, A., & Pedersen, A. (2002). Why relationships do not fit into purchasing portfolio models—A comparison between the portfolio and industrial network approaches. *European Journal of Purchasing & Supply Management, 8*(1), 35–42. http://doi.org/10.1016/S0969-7012(01)00014-4.

Dweiri, F., Kumar, S., Khan, S. A., & Jain, V. (2016). Designing an integrated AHP based decision support system for supplier selection in automotive industry. *Expert Systems with Applications, 62*, 273–283. http://dx.doi.org/10.1016/j.eswa.2016.06.030.

Dyer, J. H., & Nobeoka, K. (2000). Creating and managing a high-performance knowledge-sharing network: The Toyota case. *Strategic Management Journal, 21*(3), 345–367.

Dyer, J. H., Cho, D. S., & Chu, W. (1998). Strategic supplier segmentation: The next "best practice" in supply chain management. *California Management Review, 40*(2), 57–77. http://doi.org/10.2307/41165933.

Ferreira, L. M. D. F., Arantes, A., & Kharlamov, A. A. (2014). Development of a purchasing portfolio model for the construction industry: An empirical study. *Production Planning & Control*, 1–16 (April 2014). http://doi.org/10.1080/09537287.2014.90667..

Fisher, M. L. (1997). What is the right supply chain for your product? *Harvard Business Review*, 83–93 March-April 1997.

Gelderman, C. J., & Weele, A. J. (2003). Handling measurement issues and strategic directions in Kraljic's purchasing portfolio model. *Journal of Purchasing & Supply Management, 9*(5-6), 207–216. http://doi.org/10.1016/j.pursup.2003.07.001.

González-Benito, J. (2007). A theory of purchasing's contribution to business performance. *Journal of Operations Management, 25*(4), 901–917. http://doi.org/10.1016/j.jom.2007.02.001.

Govindan, K., Kannan, D., & Haq, A. N. (2010). Analyzing supplier development criteria for an automobile industry. *Industrial Management & Data Systems, 110*(1), 43–62. http://doi.org/10.1108/02635571011008399.

Govindan, K., Rajendran, S., Sarkis, J. &, & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production, 98*, 66–83. http://dx.doi.org/10.1016/j.jclepro.2013.06.046.

Herrera, F., & Martinez, L. (2000b). An approach for combining linguistic and numerical information based on the 2-tuple fuzzy linguistic representation model in decision-making. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 8*(5), 539–562. http://doi.org/10.1142/S0218488500000381.

Herrera, F., & Martínez, L. (2000a). A 2-tuple fuzzy linguistic representation model for computing with words. *IEEE Transactions on Fuzzy Systems, 8*(6), 746–752. http://doi.org/10.1109/91.890332.

Hilletofth, P. (2012). Differentiation focused supply chain. *Industrial Management & Data Systems, 112*(9), 1274–1291. http://doi.org/0.1108/02635571211278929.

Ho, W. (2008). Integrated analytic hierarchy process and its applications - A literature review. *European Journal of Operational Research, 186*(1), 211–228. http://doi.org/10.1016/j.ejor.2007.01.004.

Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research, 202*(1), 16–24. http://doi.org/10.1016/j.ejor.2009.05.009.

Kannan, V. R., & Tan, K. C. (2002). Supplier selection and assessment: Their impact on business performance. *Journal of Supply Chain Management, 38*(4), 11–21. http://doi.org/10.1111/j.1745-493X.2002.tb00139.x.

Karsak, E. E., & Dursun, M. (2015). An integrated fuzzy MCDM approach for supplier evaluation and selection. *Computers & Industrial Engineering, 82*, 82–93. https://doi.org/10.1016/j.cie.2015.01.019.

Kraljic, P. (1983). Purchasing must become supply management. *Harvard Business Review*, 109–117 set-oct.

Krause, D. R. (1997). Supplier development: Current practices and outcomes. *International Journal of Purchasing and Materials Management, 33*(1), 12–19. http://doi.org/10.1111/j.1745-493X.1997.tb00287.x.

Krause, D. R., Handfield, R. B., & Scannell, T. V. (1998). An empirical investigation of supplier development: Reactive and strategic processes. *Journal of Operations Management, 17*(1), 39–58. https://doi.org/10.1016/S0272-6963(98)00030-8.

Lee, D. M., & Drake, P. (2010). A portfolio model for component purchasing strategy and the case study of two South Korean elevator manufacturers. *International Journal of Production Research, 48*(22), 6651–6682. http://doi.org/10.1080/00207540902897780.

Liao, H., Xu, Z., & Zeng, X. J. (2014). Distance and similarity measures for hesitant fuzzy linguistic term sets and their application in multi-criteria decision making. *Information Sciences, 271*, 125–142. http://doi.org/10.1016/j.ins.2014.02.125.

Liao, S. H. (2005). Expert system methodologies and applications - A decade review from 1995 to 2004. *Expert Systems with Applications, 28*(1), 93–103. http://dx.doi.org/10.1016/j.eswa.2004.08.003.

Lima, F. R., Osiro, L., & Carpinetti, L. C. R. (2013). A fuzzy inference and categorization approach for supplier selection using compensatory and non-compensatory decision rules. *Applied Soft Computing, 13*(10), 4133–4147. https://doi.org/10.1016/j.asoc.2013.06.020.

Luo, X., Wu, C., Rosenberg, D., & Barnes, D. (2009). Supplier selection in agile supply chains: An information-processing model and an illustration. *Journal of Purchasing and Supply Management, 15*(4), 249–262. http://doi.org/10.1016/j.pursup.2009.05.004.

Luzzini, D., Caniato, F., Ronchi, S., & Spina, G. (2012). A transaction costs approach to purchasing portfolio management. *International Journal of Operations & Production Management, 32*(9), 1015–1042. http://doi.org/10.1108/01443571211265684.

Martínez, L., & Herrera, F. (2012). An overview on the 2-tuple linguistic model for computing with words in decision making: Extensions, applications and challenges. *Information Sciences, 207*, 1–18. https://doi.org/10.1016/j.ins.2012.04.025.

Nellore, R., & Söderquist, K. (2000). Portfolio approaches to procurement: Analyzing the missing link to specifications. *Long Range Planning, 33*(2), 245–267.

Olsen, R. F., & Ellram, L. M. (1997). A portfolio approach to supplier relationships. *Industrial Marketing Management, 26*(2), 101–113. http://doi.org/10.1016/S0019-8501(96)00089-2.

Osiro, L., Lima-junior, F. R., & Carpinetti, L. C. R. (2014). A fuzzy logic approach to supplier evaluation for development. *International Journal of Production Economics, 153*(c), 95–112. http://doi.org/10.1016/j.ijpe.2014.02.009.

Padhi, S. S., Wagner, S. M., & Aggarwal, V. (2012). Positioning of commodities using the Kraljic Portfolio Matrix. *Journal of Purchasing and Supply Management, 18*(1), 1–8. http://doi.org/10.1016/j.pursup.2011.10.001.

Pagell, M., Wu, Z., & Wasserman, M. E. (2010). Thinking differently about purchasing portfolios: An assessment of sustainable sourcing. *Journal of Supply Chain Management, 46*(1), 57–73. http://doi.org/10.1111/j.1745-493X.2009.03186.x.

Parasuraman, A. (1980). Vendor segmentation: An additional level of market segmentation. *Industrial Marketing Management, 9*(1), 59–62.

Prajogo, D., Chowdhury, M., Yeung, A. C. L., & Cheng, T. C. E. (2012). The relationship between supplier management and firm's operational performance: A multi-dimensional perspective. *International Journal of Production Economics, 136*(1), 123–130. http://doi.org/10.1016/j.ijpe.2011.09.022.

Qin, J., & Liu, X. (2016). 2-tuple linguistic Muirhead mean operators for multiple attribute group decision making and its application to supplier selection. *Kybernetes, 45*(1), 2–29. http://dx.doi.org/10.1108/K-11-2014-0271.

Rezaei, J., & Ortt, R. (2012). A multi-variable approach to supplier segmentation. *International Journal of Production Research, 50*(16), 4593–4611. http://doi.org/10.1080/00207543.2011.615352.

Rezaei, J., & Ortt, R. (2013a). Supplier segmentation using fuzzy logic. *Industrial Marketing Management, 42*(4), 507–517. http://doi.org/10.1016/j.indmarman.2013.03.003.

Rezaei, J., & Ortt, R. (2013b). Multi-criteria supplier segmentation using a fuzzy preference relations based AHP. *European Journal of Operational Research, 225*(1), 75–84. http://doi.org/10.1016/j.ejor.2012.09.037.

Rezaei, J., Wang, J., & Tavasszy, L. (2015). Linking supplier development to supplier segmentation using Best Worst Method. *Expert Systems with Applications, 42*(23), 9152–9164. http://doi.org/10.1016/j.eswa.2015.07.073.

Rodriguez, R. M., Martinez, L., & Herrera, F. (2012). Hesitant fuzzy linguistic term sets for decision making. *IEEE Transactions on Fuzzy Systems, 20*(1), 109–119. https://doi.org/10.1109/TFUZZ.2011.2170076.

Saaty, T. L. (1988). *Multicriteria decision making: The analytic hierarchy process* (2nd ed.). New York: McGraw-Hill.

Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research, 48*(1), 9–26. http://dx.doi.org/10.1016/0377-2217(90)90057-I.

Sarkis, J., & Talluri, S. (2002). A model for strategic supplier selection. *Journal of Supply Chain Management, 38*(4), 18–28. http://doi.org/10.1111/j.1745-493X.2002.tb00117.x.

Segura, M., & Maroto, C. (2017). A multiple criteria supplier segmentation using outranking and value function methods. *Expert Systems with Applications, 69*, 87–100. http://dx.doi.org/10.1016/j.eswa.2016.10.031.

Shin, H., Collier, D. A., & Wilson, D. D. (2000). Supply management orientation and supplier/buyer performance. *Journal of Operations Management, 18*(3), 317–333. http://doi.org/10.1016/S0272-6963(99)00031-5.

Subramanian, N., & Ramanathan, R. (2012). A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics, 138*(2), 215–241. http://doi.org/10.1016/j.ijpe.2012.03.036.

Tramarico, C. L., Mizuno, D., Salomon, V. A. P., & Marins, F. A. S. (2015). Analytic hierarchy process and supply chain management: A bibliometric study. *Procedia Computer Science, 55*, 441–450. http://doi.org/10.1016/j.procs.2015.07.005.

Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research, 169*(1), 1–29. http://doi.org/10.1016/j.ejor.2004.04.028.

Wagner, S. M. (2006). Supplier development practices: An exploratory study. *European Journal of Marketing, 40*(5/6), 554–571. http://doi.org/10.1108/03090560610657831.

Weber, C. A., Current, J. R., & Benton, W. C. (1991). Vendor selection criteria and methods. *European Journal of Operational Research, 50*(1), 2–18. http://doi.org/10.1016/0377-2217(91)90033-R.

Wen, X., Yan, M., Xian, J., Yue, R., & Peng, A. (2016). Supplier selection in supplier chain management using Choquet integral-based linguistic operators under fuzzy heterogeneous environment. *Fuzzy Optimization and Decision Making, 15*(3), 307–330. https://doi:10.1007/s10700-015-9228-2.

You, X-Y., You, J-X., Liu, H-C., & Zhen, Lu. (2015). Group multi-criteria supplier selection using an extended VIKOR method with interval 2-tuple linguistic information. *Expert Systems with Applications, 42*(4), 1906–1916. http://dx.doi.org/10.1016/j.eswa.2014.10.004.