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Use of fuzzy logic for measuring practices and performances of supply chain

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ABSTRACT

The objective of this research is to show an innovative way for processing the collected data and measurement of practice and performances of supply chain by means of transformation of the obtained linguistic values, using the appropriate *fuzzy* methods, into crisp values of research variable dimensions.

The methodology was applied for the measurement of the influence of an independent supply chain practice variable on the dependent supply chain performance variable and the research included the food industry companies. In order to apply the multivariate analysis methods, it is necessary to have the dimensions of the variable, but not the claims. *Fuzzy* logic enables the weighting of each claim and determining its weight, and determining the research variable dimension value in order to be able to use the multivariate analysis methods. The use of this methodology enables realistic evaluation of the dimensions and the results obtained show a statistically significant influence proving to be suitable for further testing using various statistical methods. The hypotheses about the relationships between supply chain practices and supply chain performances are confirmed.

1. Introduction

It is very difficult to measure many phenomena in the economy, especially in respect of the qualitative research. Supply chain management, as a new field of research for economists, provides a lot of examples where it is almost impossible to reach the precise evaluation of variables affecting the decision making. If we observe the measurement of supply chain practices and performances, the question is raised regarding which dimensions need to be observed and how they will be measured. The researcher, in this respect, may decide for the dimensions he/she singled out as crucial through inductive reasoning, after which by using a deductive approach, the most important indicators for measurement can be identified. The next obstacle is the fact that the measurement scales usually used for measurement of these indicators are not sufficiently precise. The Likert Scale is commonly used, but it does not provide the possibility of making precise conclusions.

In order to solve the problem of imprecision of human thinking or data, Zadeh [1] introduced the theory of *fuzzy* sets which is oriented on rational uncertainty due to imprecision and ambiguity. *Fuzzy* logic uses approximate instead of precise reasoning. Its importance can be found in the fact that human thinking is by nature approximate [2]. People often compare data according to their own reasoning, so it is difficult to generalize them. *Fuzzy* logic provides great contribution to research of unclear data and, because many actual situations cannot be clearly defined, it is close to human perception. *Fuzzy* logic allows the introduction of the mean value defined between the traditional attitudes like yes/no, true/false, black/white, etc. [3]. If we say that in the classical logic, which can be used only with the information which is completely true or false, everything is black or white, then for *fuzzy* logic we can say that everything is in the shades of grey.

In order to present *fuzzy* logic concept implementation in supply chain management, the paper will show the relation between supply chain practices and performances. For the measurement of supply chain practices in this research, we used the following dimensions: partner relationships with suppliers, customer relationships, internal integrations, and information quality and sharing. On the other side, for the measurement of supply chain performances we used the following dimensions: flexibility, agility, quality, innovation, and sustainability. The research was conducted on the sample of 135 food industry companies in Bosnia and Herzegovina (BiH). For each dimension, we determined the indicators and the surveyed companies expressed their attitudes by the Likert Scale, i.e. using a questionnaire with linguistic values. The specificity of the research is the use of the innovative methodology for data processing based on *fuzzy* logic. Namely, in order to use the methods of multivariate analysis for the analysis of the effects of the independent variable on the dependent one, it is necessary to

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have the values of specific dimensions, and not of the indicators, i.e. claims to which the participants responded. For calculation of the dimension values, it is necessary to determine the importance of each claim within the specific dimension. For objective weighting of each claim, we used the methods of *fuzzy* entropy and *fuzzy* CRITIC. In order to keep the uniformity in the analysis of the results, we used the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) method which is developed for solving the problems in deviation from the ideal positive and negative solution in the *fuzzy* environment. In this way, using the *fuzzy* approach, we made the reduction which enabled subsequent use of the multivariate analysis based on the value of dimensions, but not of the claims. The claims in this instance serve for obtaining the real value of individual dimensions of the research variables.

Hence the goal of this paper is to enable, using the hybrid method based on *fuzzy* logic and the FTOPSIS method, the verification of the following two research hypotheses:

H (*(1)***)**. The companies in the food industry with better supply chain practices have better supply chain performances.

H (*(2)***)**. The companies in the food industry have a statistically significant rank correlation between the dimensions of supply chain practices and performances.

For testing the hypotheses, we used the Multiple Regression Analysis (MRA) and Spearman's correlation coefficient.

2. Literature review

In this section, we will describe the results of some of the most significant research related to the measurement of supply chain practices and performance, i.e. application of fuzzy logic on the supply chain.

2.1. Supply chain practice

Supply chain includes all operations connecting the suppliers on the one side and the customers on the other side [4]. Li et al. [5] define supply chain practice as the set of activities undertaken in the organization for the promotion of efficient management. Previous studies observed supply chain practice with various dimensions. Ince et al. [6] used the following dimensions for the measurement of supply chain practice: strategic relationships with suppliers, partner relationships with customers and level of quality and information sharing. Besides the supply chain, they also used the Enterprise Resource Planning (ERP) in their model, and through the mutual relationship with the supply chain practice they studied their effect on the competitive advantages and performance of the company. Toyin [7] used the following supply chain practices dimensions: strategic relationships with suppliers, customer relationship, level of information sharing, level of quality of information sharing, and postponement, by which its effects on supply chain performance were measured within the companies in the processing industry. Sukati et al. [8] used the following dimensions: strategic relationships with suppliers, customer relationship, and information sharing, which they used for measuring the effects of supply chain practices on the responsible application of the supply chain and on the competitive advantages. Jabbour et al. [9] used the following dimensions: supply chain integration, information sharing, customer services management, customer relationship, supplier relationship, and postponement, which they used for studying the effects of supply chain practices on competitive advantages of the companies in the energy sector. Miguel and Brito [10] used the following dimensions: information sharing, long-term relationships, collaboration, and process integration, which they used for observing the effects on operating performances and competitive advantages by means of two models.

Flynn et al. [11], for measuring the effects of supply chain practices on the operational and business performances, used the following dimensions of supply chain practices: internal integration, customer integration, and supplier integration. Zhou et al. [12] observed supply chain practices and information quality as the instruments for strategic directing the supply chain. They observed supply chain practices by means of procurement and supply practices, while separately from supply chain practices they observed information quality. However, Mzoughi et al. [13] and Li et al. [5,14] included information quality in supply chain practice. Besides information quality, Mzoughi et al. [13] for measuring the effects of supply chain practices on the competitive advantages of the company used the following dimensions of supply chain practices: strategic supplier's partnership, customer relationships, quality of information sharing, and level of information quality. Li et al. [5], to examine the effects on the business performance and competitive advantages of the company, used the following supply chain practices dimensions: strategic supplier partnership, customer relationships, level of information sharing, quality of information, and postponement. Besides these dimensions in their study from 2005, they also used the dimension of the internal *lean* practice [14]. Bayraktar et al. [15] used the following supply chain practices dimensions: strategic collaboration and *lean* practice, supplier selection practice, and procurement practices. Barman et al. [16] used the following dimensions: strategic relationships with suppliers, customer relationships, level of information sharing, level of information quality, postponement, and internal *lean* practices.

As it can be seen from the mentioned articles, various dimensions of supply chain practices have been used, including strategic relationships by means of establishing cooperation with suppliers and customers as well as operational relationships such as internal practices and postponement. In establishing the strategic relationship with the most important suppliers and customers, the level and quality of information sharing are crucial. Therefore, in this paper, the following dimensions for supply chain practices have been used: strategic relationships with suppliers, relationships with customer, internal integrations, and the level and quality of information sharing.

2.2. Supply chain performance

In practice, there are different views of supply chain performance measurement. It is difficult to determine which activity improves supply chain performances. In the past, supply chain performances connected everything to costs [17], so the improvement of performances was in fact a decrease in costs within the supply chain. In the past, the most important thing for the companies within the supply chain was to eliminate all unnecessary costs in order to improve the performances. However, costs are not the only measure for improvement of supply chain performances and performances of a company in general. In the supply chain, it is necessary to improve business cooperation, fluctuation of materials and raw materials in the company, and production and delivery of the final products. Therefore, supply chain performances need to include a wider range of actions.

Beamon [18] suggested the framework for combining costs and other criteria, such as customer services and environmental liability and provided the guidelines for the measurement of supply chain performances. Lai et al. [17] pointed to the following dimensions which need to be taken into account in order to measure supply chain performances: time and speed, agility and flexibility, and quality and productivity. Christopher [19] explained supply chain performances by means of: responsibility, reliability, flexibility, and partner relationships. Luetić [20] measured the effect of business intelligence on the supply chain, by using the following dimensions: agility, adaptability, compatibility, proactive behavior, and performances related to return on investment, sales volume, efficiency and shortening of time. Toyin [7] used the following dimensions: flexibility, integrations, reacting to customer needs, suppliers' performances, and quality and partner relationships. Cho et al. [21] used the following dimensions to measure the performance of the services supply chain: reactions, flexibility, and reliability, while Sukati et al. [8] used integration, flexibility and reacting to the customer needs. Miguel and Brito [10] used the following dimensions for testing the effects of the supply chain on operating performances of a company: costs, flexibility, quality, and deliveries. Ganga and Carpinetti [22] measured supply chain performances by means of *fuzzy* logic and used the following dimensions: reliability, flexibility, reactions, costs, and assets. Kozarević and Puška [4] measured the relationship between the use of supply chain with partner relationships and competitiveness, and while doing so they used the following dimensions for the measurement of supply chain performances: agility, flexibility, efficiency, stability, and responsibility. Cai et al. [23] used resources, output, flexibility, innovations, and information as the dimensions, while Theeranuphattana and Tang [24] developed a conceptual model for the measurement of supply chain performances by using reactions, reliability, flexibility, and costs of assets management as the dimensions. Based on these and some other studies, it can be concluded that there are different approaches and dimensions used for the measurement of supply chain performances and this research will use the following dimensions: flexibility, agility, quality, innovation, and sustainability.

2.3. Use of fuzzy logic in supply chain

The examples of use of *fuzzy* logic in the supply chain management are: selection of supplier [25–28], risks within the supply chain [29–31], reduction of supply chain costs [32,33] and various other areas. In the remaining part of this section, we will focus on the review of the use of the FTOPSIS method in the supply chain.

Orji and Wei [27], by using hybrid FTOPSIS and *fuzzy* entropy, made the selection of a sustainable supplier. They have applied expert opinion and simulation. The simulation results showed that the increase in the rate of investments in sustainability by the supplier contributed to the increase in overall sustainability. Zouggari and Benyoucef [34], by combining the *fuzzy* Analytic Hierarchy Process (*fuzzy* AHP) method and simulation with FTOPSIS, made the selection of a supplier in group decision making. Using FTOPSIS, Chen et al. [35] made the selection of a supplier by using this method in group decision making.

Chatterjee and Kar [36] used the interval *fuzzy* logic and the FTOPSIS method and in that way ranked suppliers in conditions of uncertainty, while taking the risks faced by companies in the selection of suppliers as the criteria. Lee et al. [37] observed the problem of supplier selection with a decision maker having subjective and *fuzzy* preferences. They based the supplier selection on the selection of an agile supplier by using the Bullwhip Effect and costs of supplies. In their model, they combined the *fuzzy* AHP method with the FTOPSIS method.

Sheu [38] presented a hybrid neuro-*fuzzy* methodology for the identification of the appropriate work mode in the global management of the supply chain. The proposed methodology framework in the paper included three main development stages: establishing the strategic hierarchy for global logistics, formulating rules for identification of the global logistics model, and selecting the global logistics model. He combined the methods of *fuzzy* AHP and FTOPSIS for selection among six types of the global logistics and work modes. Rostamzadeh et al. [39] studied and compared the existing models of supply, production, and distribution in the supply chain and proposed the management model by using a genetic algorithm. In the process, they had to quantify the flow of goods and materials within the supply chain. For the development of this model, they used the methods of *fuzzy* AHP and FTOPSIS. Using simulation, they determined the most effective strategic and operating policies for an efficient supply chain system.

Mangla et al. [30] explored the risks within the supply chain by using the combination of the *fuzzy* AHP method and FTOPSIS method. Within the green supply chain, they explored the risks in the management of supply chain efficiency. Kabra and Ramesh [40] studied the obstacles to coordination in the management of a humanitarian supply chain and proposed solutions for overcoming those obstacles. In their paper, they investigated 23 obstacles to coordination grouped into five categories. In the process, they used the *fuzzy* AHP and FTOPSIS methods.

Bottani and Rizzi [41] used the FTOPSIS method to select the best provider of logistics services. In the process, they used the combination of the *fuzzy* AHP and FTOPSIS methods. Kahraman et al. [42] developed a decision-making model for evaluation and selection of the logistics information technology. In their hierarchical model, they had four main and 11 auxiliary criteria and they used the hierarchical FTOPSIS for evaluation and selection of the logistics information technology.

The use of the FTOPSIS method in the supply chain was most commonly applied in the papers on the selection of suppliers and various other service providers in the supply chain. The reason might be found in the fact that the FTOPSIS method uses multiple-criteria analysis and its goal is to rank the alternatives according to the specific criteria.

3. Theoretical grounds of fuzzy logic and the FTOPSIS method

3.1. Fuzzy logic

The theory of *fuzzy* sets provides a wider framework than the classical logic and it is directed to the development of abilities reflecting the human thinking in the real world [43]. *Fuzzy* sets and *fuzzy* logic are strong mathematical tools for modeling *fuzzy* systems in the economy, nature, and understanding of human thinking. Their role is significant when applied on the complex problems which cannot be easily described with the traditional mathematical models, especially when the goal is to find a compromise solution [44]. The theory of *fuzzy* sets is used for modeling imprecise information resulting from human thinking [45]. Since the complete information is not available, in order to make a decision, apart from the objective probabilities for the occurrence of an event, human subjectivity and *fuzzy* logic have to be taken into account.

The beginnings of the use of the *fuzzy* logic date back to 1965. In the paper *Fuzzy sets*, published in the journal Information and Control, professor Zadeh from Berkeley University has set the foundations of *fuzzy* logic, emphasizing that if we want to overcome very complex problems we do not have to move towards strictness, higher precision in descriptions and thinking about the occurrences, but we can move in the opposite direction and allow to be imprecise in spirit of natural language [1]. *Fuzzy* logic allows nuances for the grade of membership of the elements to a specific set, i.e. each element is associated with a real number as the dimension of the grade of membership of that element to a set [46].

Let us say that the set X is a universal set, and fuzzy set $\widetilde{A}$ is a subset of the set X. *Fuzzy* set $\widetilde{A}$ from the set X is defined with the membership function $\mu_{\widetilde{A}}(x)$ which connects each element x in the set X of real numbers from the interval [0,1]. The membership function $\mu_{\widetilde{A}}(x)$ is called grade of membership of the elements x to *fuzzy* set $\widetilde{A}$ [1].

Two *fuzzy* sets $\widetilde{A}$ and $\widetilde{B}$ are equal if [2]:

$$\forall\, x_i \in X,\ \mu_{\widetilde{A}}(x) = \mu_{\widetilde{B}}(x) \tag{1}$$

For *fuzzy* set $\widetilde{A}$ we say that it is a subset of *fuzzy* set $\widetilde{B}$ if and only if the following is valid [47]:

$$\forall\, x_i \in X,\ \mu_{\widetilde{A}}(x) \le \mu_{\widetilde{B}}(x) \tag{2}$$

Fuzzy set $\widetilde{A}$ is normal in the universal set X if:

$$\exists\, x_i \in X,\ \mu_{\widetilde{A}}(x_i) = 1 \tag{3}$$

Fuzzy set $\widetilde{A}$ of the subset X is convex if and only if for all x_1, x_2 in the universal set X [48]:

$$\mu_{\widetilde{A}}(\lambda x_1 + (1-\lambda)x_2) \ge Min(\mu_{\widetilde{A}}(x_1), \mu_{\widetilde{A}}(x_2)), \quad where\ \lambda \in [0, 1] \tag{4}$$

The highest value of *fuzzy* number in the *fuzzy* set $\widetilde{A}$ subset of set X when it is normalized assumes the value one.

For triangular *fuzzy* number $\tilde{n}$ (a, b, c) the membership function is defined as:

$$\mu_A(x) = \begin{cases} 0,\ x < a \\ \frac{(x-a)}{(b-a)},\ a \le x \le b \\ \frac{(c-x)}{(c-b)},\ b \le x \le c \\ 0,\ x > c \end{cases} \tag{5}$$

Based on this, it is concluded that each *fuzzy* set $\widetilde{A}$ is completely and uniquely defined by its membership function. According to the *fuzzy* theory, selection of the membership function, i.e. the function shape and confidence interval width, is most frequently done on the basis of subjective assessment or an experience [3].

In the situations which are too complex or not properly defined to evaluate them with quantitative expressions, linguistic values are used. The linguistic values are values expressed in linguistic terms [49]. As statistical analysis cannot be applied on linguistic values, they need to be transformed to appropriate *fuzzy* numbers by using the membership function. The application of *fuzzy* logic enables the application of the statistical analysis. In this research, we will use linguistic values for determining the agreement with certain claims during the measurement of the research dimensions in the interval from strongly disagree to strongly agree, where we will use the scale with 5 membership grades.

The links between linguistic values and membership functions defined by *fuzzy* numbers in the range from one to nine are shown in Fig. 1.

The links between membership functions and the corresponding *fuzzy* numbers is shown in Table 1, which represents a transformation of linguistic values to the corresponding *fuzzy* numbers using the membership function.

Based on this transformation, the membership functions of the *fuzzy* numbers are formed. Let us take, for example, the claim DA. The membership function for this claim is as follows:

$$\mu_{\text{Disagree}}(x) = \begin{cases} 0,\ x < 2 \\ \frac{(x-2)}{(3-2)},\ 2 \le x \le 3 \\ 1,\ x = 3 \\ \frac{(4-x)}{(4-3)},\ 3 \le x \le 4 \\ 0,\ x > 4 \end{cases} \tag{6}$$

For the claim SD, the membership function is as follows:

$$\mu_{\text{Stronglydisagree}}(x) = \begin{cases} 0,\ x < 8 \\ \frac{(x-8)}{(9-8)},\ 8 \le x \le 9 \\ 1,\ x = 9 \end{cases} \tag{7}$$

The membership functions for other linguistic values are formed in a similar manner.

If $\widetilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ are two triangular *fuzzy* numbers of the *fuzzy* set $\widetilde{A}$ of the subset X. The distance between these two *fuzzy* numbers is defined as [48]:

$$d(\widetilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \tag{8}$$

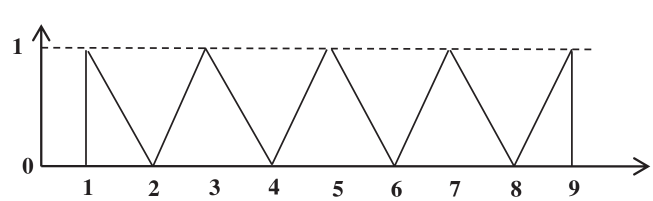

Fig. 1. Membership of linguistic values to membership functions.

Table 1
Transformation of the linguistic values to *fuzzy* numbers.

Linguistic variable	*Fuzzy* number
Strongly disagree (SD)	(1, 1, 2)
Disagree (DA)	(2, 3, 4)
Neither agree or disagree (AD)	(4, 5, 6)
Agree (AG)	(6, 7, 8)
Strongly agree (SA)	(8, 9, 9)

Weighted mean represents the integration of the triangular *fuzzy* number $\widetilde{m} = (m_1, m_2, m_3)$ and it is defined as [50]:

$$P(\widetilde{m}) = \frac{1}{6}(m_1 + 4m_2 + m_3) \tag{9}$$

With the application of the weighted mean, triangular *fuzzy* number can be transformed to a crisp value, i.e. it is defuzzified.

3.2. Fuzzy TOPSIS method

The transformation of the multi-criteria analysis method TOPSIS (*Technique for Order Performance by Similarity to Ideal Solution*) to FTOPSIS was done with the application of *fuzzy* logic. Chen and Hwang [51] were the first ones to make this transformation so that the values of alternatives and criteria weight could be expressed by means of linguistic values. The first step of the FTOPSIS method is forming the initial decision matrix and determining the values of alternatives and criteria weight.

The elements of the decision matrix are $X = \{x_{ij},\ i = 1, 2, ..., m;\ j = 1, 2, ..., n\}$, where each individual element x_{ij} is formed using linguistic values $x_{ij} = (a_{ij}, b_{ij}, c_{ij})$. The criteria weights are determined for each criteria W $(w_1, w_2, ..., w_j)$ on the basis of *fuzzy* numbers, so $w_j = (w_{j1}, w_{j2}, w_{j3})$. Based on this, the initial decision matrix is formed, which is represented by the following expression:

$$D = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \\ w_1 & w_2 & \cdots & w_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{10}$$

In order for all matrix elements to have the same dimensions, it is necessary to normalize it, and different procedures can be used for that [48,52–54]. In linear normalization of type 1, i.e. simple linear normalization, the following relations for maximization are formed:

$$r_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right) \tag{11}$$

and relations for minimization:

$$r_{ij} = \left(\frac{a_j^+}{c_{ij}}, \frac{a_j^+}{b_{ij}}, \frac{a_j^+}{a_{ij}}\right), \tag{12}$$

where c_j^+ is the maximum value of the *fuzzy* number, and a_j^+ minimum value of the *fuzzy* number. During normalization, it is necessary to take care that the relation between the *fuzzy* numbers remains $a_{ij} \le b_{ij} \le c_{ij}$. The elements of the normalized decision matrix are multiplied by corresponding weights and the weighted decision matrix is formed, with the following elements $r_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

After that, n-dimensional Euclidean distances for all the alternatives of the ideal positive solution are calculated:

$$A^+ = (v_1^+, v_2^+, ..., v_n^+), \quad \textit{where } v_j^+ = \left(\max_i v_{ij}\right) \tag{13}$$

and of ideal negative solution

$$A^- = (v_1^-, v_2^-, ..., v_n^-), \quad \text{where } v_j^- = \left(\min_i v_{ij}\right) \tag{14}$$

Distance of each alternative from A^+ and A^- can be calculated as [35]

$$d_i^+ = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^+), \; i = 1, 2, ..., m \tag{15}$$

$$d_i^- = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^-), \; i = 1, 2, ..., m \tag{16}$$

where $d_v(\tilde{v}_{ij}, \tilde{v}_j^-)$ is measure of distance between two fuzzy numbers [48]

$$d_v(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{3}[(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2]} \tag{17}$$

In the end, relative distance is determined for each alternative on the basis of the expression

$$Q_i = \frac{d_i^-}{d_i^+ + d_i^-}, \; i = 1, 2, ..., m \tag{18}$$

where Q_i represents the result of the FTOPSIS method and it is in the range $0 \le Q_i \le 1$. The closer the alternative A_i is to the ideal solution, the closer the value of Q_i to one.

4. Methodology

The specificity of the research is the use of an innovative methodology for data processing shown in Fig. 2. A questionnaire was used for the measurement of the research variables, in which the research variables consisted of the dimensions which included a specific number of claims represented by linguistic values. The companies expressed their attitudes towards the claims in form of linguistic values which had to be transformed into crisp values. The reliability of the measurement scale was tested by using *Cronbach's alpha* coefficient. In order to calculate the value of dimensions using the FTOPSIS method, it is necessary to determine the importance of each claim within a specific dimension. For objective evaluation of the weight of each claim we can use the *fuzzy* entropy and *fuzzy* CRITIC methods. With the Multivariate Analysis of Variance (MANOVA) the results obtained by both methods were compared and the conclusion was reached that there is no statistically significant difference in the obtained weights. For this reason, this paper will present only the results reached by using the *fuzzy* entropy, while the procedure of *fuzzy* CRITIC can be seen in Agarski [55]. For testing the research hypotheses, statistical analysis methods were used, i.e. MRA and Spearman's correlation coefficient.

The detailed procedure for the transformation of linguistic values into crisp values is shown in Fig. 3.

The membership function and transformation of linguistics values into triangular *fuzzy* numbers were used for transformation of linguistic values to *fuzzy* numbers. A special focus in the methodology was paid to:

- Transformation of the obtained linguistic values into *fuzzy* numbers and calculation of the dimension values using the appropriate *fuzzy* methods, with the importance of each particular claim determined within the individual dimensions of the variables by using objective methods for weighting (*fuzzy* entropy).
- Ranking of companies inside the individual dimensions within the research variables and determining their relations.
- Examination of the dependence of research variables by using multivariate analysis.
- Calculation of Spearman's correlation coefficients on the rankings obtained by the FTOPSIS method.

5. Results and discussion

5.1. Descriptive analysis

Tables 2 and 3 show the results of the descriptive analysis for the variables supply chain practice and performances, as well as the Cronbach's alpha values which confirm the reliability of the measurement scales.

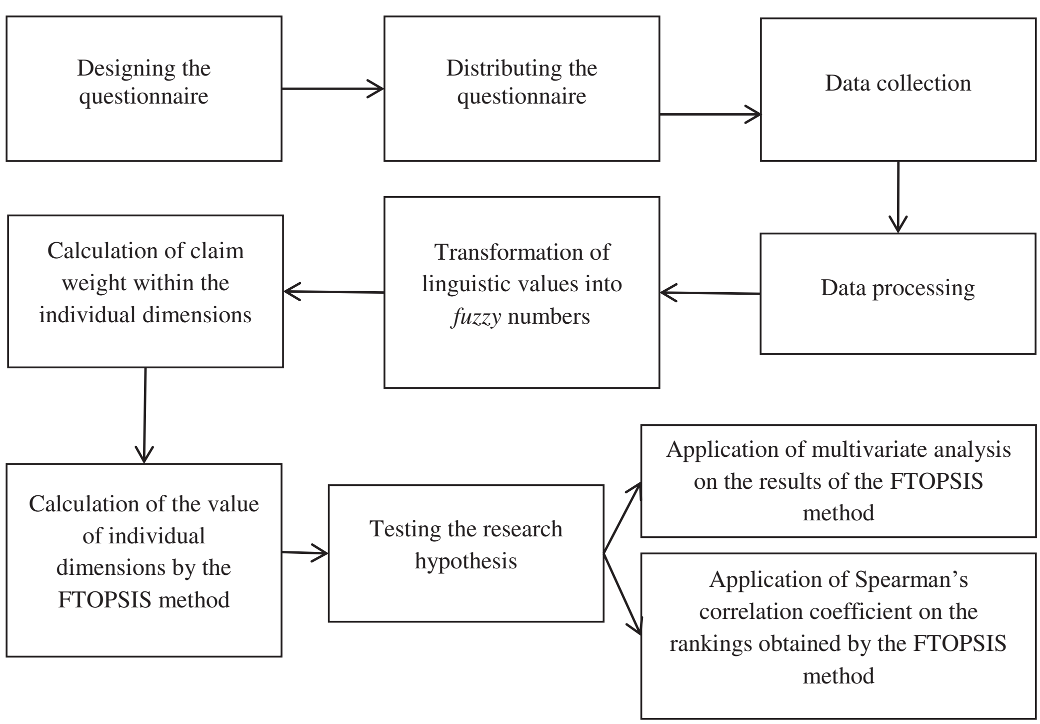

Fig. 2. Research methodology.

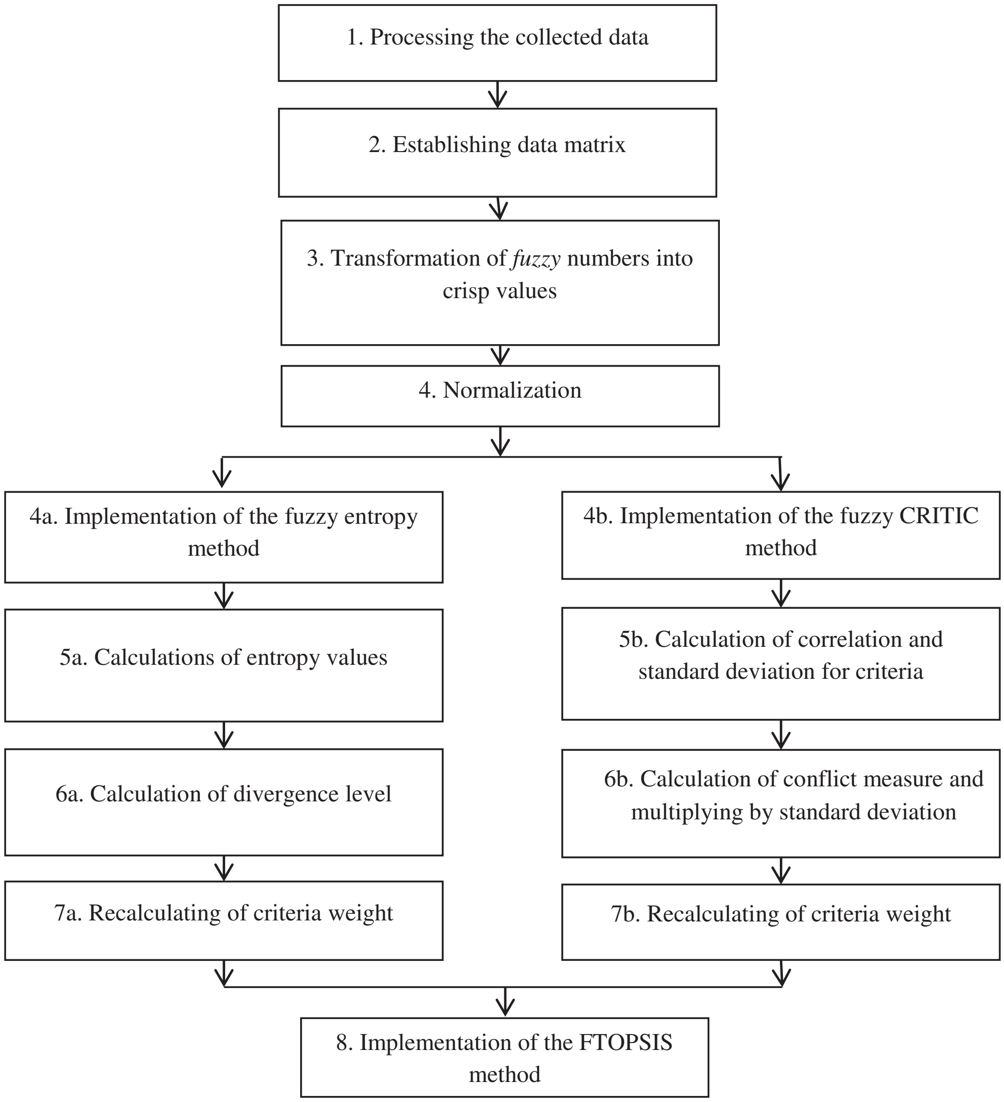

Fig. 3. The procedure of transformation of linguistics values into crisp values.

5.2. Fuzzy TOPSIS

This section of the paper uses the example of the dimension PRS, and explains how the transformation of linguistic values into crisp values was done by using *fuzzy* logic. For this purpose, with the use of abbreviations from Table 1 due to space limitations, Table 4 shows the abbreviated initial matrix with linguistic values for the first five companies only, for which the remaining procedure will also be explained.

Linguistic values, described in Table 1 by using the membership function, were transformed into appropriate *fuzzy* numbers, and this is shown in Table 5.

By using expression 9, we defuzzified *fuzzy* numbers to crisp values shown in Table 6 [56,57].

In order to use the FTOPSIS method and to calculate the dimension values, it is necessary to determine the importance of each claim within the specific dimension, by using the *fuzzy* entropy method. For that purpose, the defuzzified matrix from Table 6 needs to be normalized by having each of its elements divided by the highest value for each claim (8.833). The resulting values are shown in Table 7.

The value of entropy e_j for each claim is determined with the use of the normalized decision matrix. The value of entropy is calculated on the basis of the expression

$$e_j = -k \sum_{i=1}^{n} r_{ij} \ln r_{ij},\ j = 1, 2, \ldots, m. \tag{19}$$

where r_{ij} represents the elements of the normalized decision matrix from Table 7, and k represents the constant.

The introduction of the constant k, which is calculated on the basis of the formula $k = 1/\ln n$, provides for the values of entropy (e_j) to be in the range from zero to one [55]. Also, we are reminding that in the previous tables we showed the data for the five companies only, i.e. that $n = 135$.

After the value of entropy is calculated, the level of divergence (d_j) for each claim is calculated in relation to the average quantity of information included in each of the criteria [58]. This is calculated with the expression:

$$d_j = 1 - e_j,\ j = 1, 2, \ldots, m. \tag{20}$$

The higher the value of divergence of the initial criteria values for the criterion j, the higher the value of the level of divergence (d_j), so it is concluded that the importance of the criterion (C_j) for the problem of decision making is higher. If all the levels of divergence values are similar for a specific criterion, then that criterion is less important for the problem of decision making [59]. The deviation of certain values of

Table 2
Descriptive analysis of supply chain practices based on linguistic values and the Likert scale from 1 to 5.

Claim	SD 1	DA 2	AD 3	AG 4	SA 5	Mean	S.D.	Cronbach's alpha
Partner relationships with suppliers - PRS (Mean = 3.38; S.D. = 1.076)								
We use the help of suppliers for solving the problems in the company	11 (8.1%)	28 (20.7%)	32 (23.7%)	51 (37.8%)	13 (9.6%)	3.20	1.125	
We improve the quality of our products with the help of suppliers	4 (3.0%)	13 (9.6%)	22 (16.3%)	75 (55.6%)	21 (15.6%)	3.71	0.945	
We include suppliers in the development of new products and business processes in the company	10 (7.4%)	23 (17.0%)	26 (19.3%)	53 (39.3%)	23 (17.0%)	3.41	1.174	0.843
Together with suppliers we work on the improvement of the company business	10 (7.4%)	23 (17.0%)	42 (31.1%)	49 (36.3%)	11 (8.1%)	3.21	1.059	
Partner relationships with customers - RWC (Mean = 4.20; S.D. = 0.794)								
In the interactions with customers we work on the improvement of reliability and responsibility of the company business	1 (0.7%)	3 (2.2%)	7 (5.2%)	70 (51.9%)	54 (40.0%)	4.28	0.729	
We have built the customer relationship which is based on mutual trust	0 (0.0%)	3 (2.2%)	5 (3.7%)	64 (47.4%)	63 (46.7%)	4.39	0.669	0.789
We frequently measure the level of satisfaction of our customers	3 (2.2%)	8 (5.9%)	19 (14.1%)	68 (50.4%)	37 (27.4%)	3.95	0.925	
We try to anticipate customers' future expectations	2 (1.5%)	3 (2.2%)	19 (14.1%)	59 (43.7%)	52 (38.5%)	4.16	0.854	
Internal integrations - INI (Mean = 4.14; S.D. = 0.755)								
We use information systems in the functioning of the supply chain	4 (3.0%)	16 (11.9%)	17 (12.6%)	71 (52.6%)	27 (20.0%)	3.75	1.005	
Team work and openness are requested from employees and mutual communication is encouraged	0 (0.0%)	2 (1.5%)	3 (2.2%)	64 (47.4%)	66 (48.9%)	4.44	0.618	
Different parts of the functional organization work together on the improvement of the supply chain	1 (0.7%)	3 (2.2%)	16 (11.9%)	75 (55.6%)	40 (29.6%)	4.11	0.750	0.692
Coordination of activities is done for all plants in order to minimize the unnecessary costs	0 (0.0%)	2 (1.5%)	9 (6.7%)	76 (56.3%)	48 (35.6%)	4.26	0.646	
Information quality and sharing - IQS (Mean = 3.80; S.D. = 0.873)								
Partners share with us the information needed for the improvement of the cooperation	4 (3.0%)	6 (4.4%)	33 (24.4%)	81 (60.0%)	11 (8.1%)	3.66	0.812	
Partners share with us the crucial knowledge on development of our business processes and products	5 (3.7%)	12 (8.9%)	49 (36.3%)	60 (44.4%)	9 (6.7%)	3.41	0.884	0.884
Together with our partners, we share the information which help us in planning future activities	5 (3.7%)	7 (5.2%)	32 (23.7%)	78 (57.8%)	13 (9.6%)	3.64	0.868	
Communication with our partners is timely, accurate, complete, adequate, and reliable	4 (3.0%)	7 (5.2%)	34 (25.2%)	64 (47.4%)	26 (19.3%)	3.75	0.928	

fuzzy numbers from the specific criteria, i.e. claims, is calculated by using the level of divergence.

We calculate the final weight of each claim within the dimension w_j using the expression

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{21}$$

For the dimension PRS, the weight calculation by using the entropy method is briefly described in Table 8.

With the implementation of the previous procedure to all dimensions, we obtained the results presented in Table 9 which shows the weights for all claims. The claims with the higher diversity of the company positions also have the higher weight.

Now, the previously described procedure of the FTOPSIS method can be applied on the initial decision matrix, partially shown in Table 5 for the dimension PRS with the determined weights for individual claims for dimensions from Table 9. After the normalization of the matrix from Table 5 in accordance to expression 11, we get the matrix shown in Table 10, and after multiplying its elements with corresponding weights, a new weighted decision matrix is formed, shown in Table 11.

We finalize the procedure of transformation of linguistic into crisp values using the FTOPSIS by the calculation of Euclidian distance and relative proximity of the alternatives to the ideal solutions using expressions 15–18, as shown in Table 12.

5.3. Testing of the hypotheses

In order to test the influence of the independent variable of the supply chain practice on the dependent variable of the supply chain performance by using MRA, it is necessary to verify if the linearity condition is met by means of the correlation analysis. The results obtained using the Pearson's correlation analysis (Table 13) show that three relations do not have a significant level of correlation, as follows: PRS with FLE ($r = 0.081$) and AGI ($r = 0.048$) and IQS with SUS ($r = 0.142$). For all the other remaining relations, there is a statistically significant correlation. The correlation result is lower than 0.7, and this meets the condition of linearity in the implementation of MRA.

The results of the aggregate MRA model (Table 14) show that there is a statistically very significant influence of the supply chain practices variable on the performance of the supply chain ($p = 0.0056$, $F = 3.8350$). There is a significant correlation between the variables, which is shown by the multiple correlation analysis ($R = 0.3249$). This model with the use of the independent supply chain practices variable explained 10.55% of the supply chain performance variable ($R^2 = 0.1055$). The value of standard error in this model is low. Based on this, it can be concluded that the model is representative and valid and we can accept the first hypothesis of the research that the companies with better supply chain practice achieved better performances within the supply chain.

The results of the partial influence of individual dimensions of the supply chain practices variable on the performances of the supply chain show that none of the dimensions used shows statistically significant influence on the supply chain performance variable. The dimension RWC has the highest influence ($p = 0.0757$, $T = 1.7906$), while the dimension Partner relationships with suppliers has the lowest influence on the supply chain performance variable ($p = 0.4907$, $T = -0.6911$). At the same time, this dimension has a negative influence on the direction of the regression function ($B = -0.0558$), while other dimensions have a positive influence on the direction of the regression function. The dimension INI ($B = 0.2096$) has the highest influence on the direction of the regression function. The value of the standard error for these dimensions is low, so it can be concluded that this model is representative and valid.

On the basis of the results of the FTOPSIS method, we have ranked

Table 3
Descriptive analysis of the supply chain performance based on linguistics values and the Likert scale from 1 to 5.

Claim	SD 1	DA 2	AD 3	AG 4	SA 5	Mean	S.D.	Cronbach's alpha
Flexibility - FLE (Mean = 3.94; S.D. = 0.840)								
We can adjust our supplies at any moment	0 (0.0%)	18 (13.3%)	23 (17.0%)	74 (54.8%)	20 (14.8%)	3.71	0.880	
We can change our production in accordance to the needs	2 (1.5%)	12 (8.9%)	21 (15.6%)	68 (50.4%)	32 (23.7%)	3.86	0.932	
We develop products in accordance to customers' requests	0 (0.0%)	2 (1.5%)	17 (12.6%)	75 (55.6%)	41 (30.4%)	4.15	0.686	0.773
We can change the product delivery schedule for the customers	0 (0.0%)	7 (5.2%)	17 (12.6%)	74 (58.8%)	37 (27.4%)	4.04	0.781	
Agility - AGI (Mean = 3.83; S.D. = 0.851)								
We can adjust our supplies at any moment	1(0.7%)	13 (9.6%)	25 (18.5%)	76 (56.3%)	20 (14.8%)	3.75	0.853	
We can adjust to customers' demands very quickly	1 (0.7%)	9 (6.7%)	22 (16.3%)	73 (54.1%)	30 (22.2%)	3.90	0.845	0.859
We can offer new products to the customers very quickly	2 (1.5%)	17 (12.6%)	34 (25.2%)	55 (40.7%)	27 (20.0%)	3.65	0.987	
Innovativeness - INN (Mean = 3.80; S.D. = 0.938)								
We use modern technology for product development	2 (1.5%)	12 (1.5%)	33 (24.4%)	51 (37.8%)	37 (27.4%)	3.81	0.989	
We are technologically competitive	0 (0.0%)	18 (13.3%)	35 (25.9%)	55 (40.7%)	27 (20.0%)	3.67	0.945	0.830
We use modern warehouses and means of transport in order to have optimum quality of our products	1 (0.7%)	8 (5.9%)	25 (18.5%)	66 (48.9%)	35 (25.9%)	3.93	0.866	
Quality - QUA (Mean = 4.18; S.D. = 0.729)								
We receive feedback from customers about the quality of our products	0 (0.0%)	3 (2.2%)	11 (8.1%)	75 (55.6%)	46 (34.1%)	4.21	0.684	
We cooperate with suppliers to improve the quality of raw materials and products	1 (0.7%)	5 (3.7%)	10 (7.4%)	75 (55.6%)	44 (32.6%)	4.16	0.771	0.716
All employees are involved in the improvement of the quality of products	1 (0.7%)	3 (2.2%)	12 (8.9%)	77 (57.0%)	42 (31.1%)	4.16	0.732	
Sustainability - SUS (Mean = 4.07; S.D. = 0.751)								
In every supply chain stage we try to minimize the consumption of all resources of the company	1 (0.7%)	7 (5.2%)	15 (11.1%)	76(56.3%)	36 (26.7%)	4.03	0.810	
We minimize raw materials waste in production	0 (0.0%)	1 (0.7%)	19(14.1%)	72 (53.3%)	43 (31.9%)	4.16	0.682	
We minimize the consumption of energy and water in production	1 (0.7%)	4 (3.0%)	21 (15.6%)	84 (62.2%)	25 (18.5%)	3.95	0.726	0.790
We optimize transport in order to reduce the consumption of energy sources	1 (0.7%)	3 (2.2%)	17 (12.6%)	71 (52.6%)	43 (31.9%)	4.13	0.767	

the companies according to dimensions of the research variables and we have determined the correlation of their rankings as well as the aggregation for each variable. Since the data is in the form of ranking, we used the non-parametric correlation test Spearman's correlation coefficient. The results of this analysis show that there is a statistically significant correlation of rankings of the supply chain practices and performances variables ($r = 0.627$, $p < 0.01$), whereby the second research hypothesis is confirmed.

Spearman's correlation coefficients (Table 15) show that there is no statistically significant correlation between the dimension PRS and the dimensions FLE ($r = 0.120$, $p > 0.05$) and AGI ($r = 0.065$, $p > 0.05$). For all other dimensions, the statistically significant correlation exists. The highest level of correlation is evident with the dimensions INI and INN ($r = 0.483$, $p < 0.01$), while the lowest correlation is with the dimensions PRS and AGI ($r = 0.065$). A positive correlation exists for all dimensions.

5.4. Discussion

The results obtained from the descriptive analysis of the conducted research, show that the companies use RWC and INI more than IQS and PRS. The companies use PRS ($\overline{X} = 3.38$) the least, while RWC is used the most ($\overline{X} = 4.20$). On the basis of these results as well as the individual results for claims within these dimensions, it can be concluded that the companies in the food industry in BiH pay more attention to customers than to suppliers. However, in order to have normal operations, it is very important to build partner relationships with suppliers as well, as they supply the companies with production materials, raw materials, equipment and other things necessary for production. The results of the descriptive analysis show the lowest dispersion for the answers received for the dimension INI (S.D. = 0.755), while the highest dispersion is for the answers for the dimension PRS (S.D. = 1.076). However, some other studies revealed different relations for the dimensions of the supply chain variables. Li et al. [5], for example, obtained the results of the descriptive analysis on a sample of the American processing companies which show that the companies use PRS more than IQS, while this dimension is less used in RWC. On an example of the companies in electrical power industry in Malaysia, Sundram et al. [60] obtained the results that PRS are used more when compared to RWC and IQS. Using the example of the companies in the processing industry, Chavez et al. [61] obtained similar results. If we compare these results, we can see that certain dimensions of supply chain practices are used differently depending on the industry to which the companies belong and depending on the country where those companies are located.

The results of the descriptive analysis for the dimensions of the supply chain performance variable show that the companies in the food industry pay most attention to the improvement of quality of the supply chain ($\overline{X} = 4.17$), while the least attention is paid to innovations in the supply chain ($\overline{X} = 3.78$). However, the gap between these dimensions is not large as it was for the supply chain practices variable. All companies equally try to improve the supply chain performances. However, as there is no single research that so far used all these supply chain performances, it is not possible to integrally compare the obtained results with other results, but only individual dimensions of the supply chain performances. Miguel and Brito [10] used the dimensions of QUA and FLE, but they did not present the results of the descriptive analysis which would enable the comparison of their results with the ones from this research. Cai et al. [23] used INN and FLE, but they did not survey the companies, but rather used the decision model using the AHP method, while Ganga and Carpinetti [22] used *fuzzy* logic. In their paper, Kozarević and Puška [4] showed, on the example of companies in the processing industry in Croatia, that those companies achieved better values for AGI than for FLE in the use of the supply chain. This research did not confirm their results, because the results obtained here show that the companies in the food industry in BiH achieved better

Table 4
Initial data matrix.

Company	Claim 1	Claim 2	Claim 3	Claim 4
1	DA	AG	DA	AD
2	AG	AG	AG	AG
3	AD	AG	AG	AG
4	DA	DA	SA	AG
5	AG	SA	SA	SA

Table 5
Initial decision matrix in the form of *fuzzy* numbers.

Company	Claim 1	Claim 2	Claim 3	Claim 4
1	(2, 3, 4)	(6, 7, 8)	(2, 3, 4)	(4, 5, 6)
2	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)
3	(4, 5, 6)	(6, 7, 8)	(6, 7, 8)	(6, 7, 8)
4	(2, 3, 4)	(2, 3, 4)	(8, 9, 9)	(6, 7, 8)
5	(6, 7, 8)	(8, 9, 9)	(8, 9, 9)	(8, 9, 9)

Table 6
Defuzzified decision matrix.

Company	Claim 1	Claim 2	Claim 3	Claim 4
1	3	7	3	5
2	7	7	7	7
3	5	7	7	7
4	3	3	8.833	7
5	7	8.833	8.833	8.833

Table 7
Normalized decision matrix for the entropy method.

Company	Claim 1	Claim 2	Claim 3	Claim 4
1	0.3396	0.7925	0.3396	0.5661
2	0.7925	0.7925	0.7925	0.7925
3	0.5661	0.7925	0.7925	0.7925
4	0.3396	0.3396	1.0000	0.7925
5	0.7925	1.0000	0.9997	1.0000

Table 8
Procedure for the calculation of weights using the entropy method.

Formulas	Claim 1	Claim 2	Claim 3	Claim 4
$\sum_{i=1}^{n} r_{ij} \ln r_{ij}$	−32.9191	−26.7482	−29.2541	−33.6704
$e_j = -k \sum_{i=1}^{n} r_{ij} \ln r_{ij}$	6.7110	5.4529	5.9638	6.8641
$d_j = 1 - e_j$	−5.7110	−4.4529	−4.9638	−5.8641
w_j	0.2721	0.2121	0.2365	0.2794

Table 9
Weights of claims for dimensions obtained with the use of the entropy method.

Dimensions	Claim 1	Claim 2	Claim 3	Claim 4
Partner relationships with suppliers (PRS)	0.272	0.212	0.236	0.279
Relationship with customer (RWC)	0.222	0.183	0.333	0.262
Internal integrations (INI)	0.359	0.150	0.269	0.222
Level of information quality and sharing (IQS)	0.247	0.286	0.245	0.222
Flexibility (FLE)	0.307	0.261	0.204	0.227
Agility (AGI)	0.345	0.298	0.357	–
Innovativeness (INN)	0.325	0.375	0.300	–
Quality (QUA)	0.320	0.336	0.343	–
Sustainability (SUS)	0.255	0.226	0.290	0.229

Table 10
Normalized initial *fuzzy* decision matrix for the FTOPSIS method.

Company	Claim 1	Claim 2	Claim 3	Claim 4
1	0.250 0.333 0.444	0.750 0.778 0.889	0.250 0.333 0.444	0.500 0.556 0.667
2	0.750 0.778 0.889	0.750 0.778 0.889	0.750 0.778 0.889	0.750 0.778 0.889
3	0.500 0.556 0.667	0.750 0.778 0.889	0.750 0.778 0.889	0.750 0.778 0.889
4	0.250 0.333 0.444	0.250 0.333 0.444	1.000 1.000 1.000	0.750 0.778 0.889
5	0.750 0.778 0.889	1.000 1.000 1.000	1.000 1.000 1.000	1.000 1.000 1.000

Table 11
Weighted normalized initial *fuzzy* decision matrix for the FTOPSIS method.

Company	Claim 1	Claim 2	Claim 3	Claim 4
1	0.07 0.09 0.12	0.16 0.16 0.19	0.06 0.08 0.11	0.14 0.16 0.19
2	0.20 0.21 0.24	0.16 0.16 0.19	0.18 0.18 0.21	0.21 0.22 0.25
3	0.14 0.15 0.18	0.16 0.16 0.19	0.18 0.18 0.21	0.21 0.22 0.25
4	0.07 0.09 0.12	0.05 0.07 0.09	0.24 0.24 0.24	0.21 0.22 0.25
5	0.20 0.21 0.24	0.21 0.21 0.21	0.24 0.24 0.24	0.28 0.28 0.28

results for FLE compared to AGI.

In order to keep these claims in the further analysis, it was necessary to determine the reliability of the measurement scale of the collected data, and the *Cronbach's alpha* indicator was used for testing the reliability. The analysis of the independent supply chain practice variable showed the lowest reliability of the measurement scale for the dimension INI ($\alpha = 0.692$). However, since this value is slightly under the level set for acceptability (0.008), this dimension remained in the further analysis. For all dimensions of the dependent supply chain performance variable, *Cronbach Alpha* is over the set level, thus confirming that the measurement scales are reliable.

The results of the aggregate MRA model show that there is a statistically very significant influence of the supply chain practices variable on the supply chain performances ($p = 0.0056$, $F = 3.8350$), but also that there is no statistically significant influence of certain dimensions of supply chain practices on supply chain performances. The dimension PRS has a negative influence on the direction of the regression function. The results of the research by Sukati et al. [8] showed that a positive and significant influence on supply chain performances exists in all dimensions of supply chain practices, but in their research, they used other dimensions of the supply chain performances.

The results obtained with the use of Spearman's correlation coefficient in rankings of the research dimensions showed that for the dimension PRS the correlation is least present. Specifically, it was determined that there is no statistically significant correlation between this dimension and the dimensions of FLE and AGI. For all other dimensions, the results showed their statistically significant correlation, thus confirming the results obtained with the use of MRA.

Managerial implications of the research can be seen on two ways. First, the result will help to the managers in BiH food processing industry to improve their supply chain performances and make their

Table 12
Values of the FTOPSIS method for the dimension PRS.

Company	d_i^-	d_i^*	FTOPSIS
1	0.053 0.139 0.046 0.118	0.180 0.043 0.157 0.121	0.4156
2	0.178 0.139 0.154 0.182	0.055 0.043 0.048 0.057	0.7624
3	0.115 0.139 0.154 0.182	0.117 0.043 0.048 0.057	0.6898
4	0.053 0.041 0.201 0.182	0.180 0.140 0.000 0.057	0.5586
5	0.178 0.180 0.201 0.237	0.055 0.000 0.000 0.000	0.9349

Table 13
Correlation of supply chain practices and performances.

	PRS	RWC	INI	IQS
FLE	0.081	0.275**	0.262**	0.206*
AGI	0.048	0.334**	0.307**	0.268**
INN	0.301**	0.399**	0.492**	0.385**
QUA	0.491**	0.451**	0.430**	0.424**
SUS	0.173*	0.349**	0.443**	0.142

Correlation significance level: * 0.05; ** 0.01.

Table 14
Influence of supply chain practice on supply chain performances.

Aggregate regression model: $R = 0.3249$; $R^2 = 0.1055$; Adjusted $R^2 = 0.0780$; $F(4.130) = 3.8350$; $p = 0.0056$; standard error evaluation = 0.19144

Model	Non-standard coefficients		*T*-test	Significance (*p*-value)
	B	Standard error		
(Model constant)	**0.3425**	**0.0905**	**3.7829**	**0.0002**
PRS	−0.0558	0.0808	−0.6911	0.4907
RWC	0.2065	0.1153	1.7906	0.0757
INI	0.2096	0.1184	1.7702	0.0790
IQS	0.0784	0.1025	0.7653	0.4455

Table 15
Rank correlation of the supply chain practices and performances variables.

	PRS	RWC	INI	IQS
FLE	0.120	0.300**	0.267**	0.254**
AGI	0.065	0.378**	0.305**	0.348**
INN	0.294**	0.405**	0.483**	0.475**
QUA	0.420**	0.434**	0.418**	0.320**
SUS	0.235**	0.302**	0.428**	0.210*

Correlation significance level: * 0.05; ** 0.01.

business more competitive. The obtained results indicated which supply chain practice dimensions do not affect supply chain performance, so that managers should focus more to these dimensions in order to improve business operations. Second, this new approach to the analysis of linguistic answers, which can be easily provided from the survey of the company's buyers and suppliers, can be used as very effective tool for permanent managerial quality control of supply chain management efficiency in the company.

6. Conclusion

The presented research offers an innovative method for processing collected data and measuring the research variables by means of transformation of linguistic answers, using *fuzzy* logic and the FTOPSIS method, to crisp values of the dimensions of the research variables. In order to make this transformation, a methodology framework was shaped for the transformation of quality claims expressed with linguistic values to crisp values. With the use of the FTOPSIS method, the values of variable dimensions were calculated, which were in the range from zero to one. Higher values of the dimensions point to the dimensions which are used more by the company. The methodology was used for the measurement of influence of the independent supply chain practices variable on the dependent supply chain performances variable for the companies in the food industry. The use of this methodology enabled realistic evaluation of the dimensions and the obtained results are suitable for further testing by using various statistical and multivariate analysis methods. The application of the research model determined that there is a statistically significant influence of the practices on the performances of the supply chain. The applied methodology is innovative and it is possible to apply it on various problems where data collection for dimensions of research variables is done by means of claims to which participants respond in the form of the linguistic values.

References

[1] Zadeh LA. Fuzzy sets. Inf. Control 1965;8(3):338–53. https://doi.org/10.1109/2.53.
[2] Škrbić S. Use of fuzzy logic in relation data bases. Faculty for natural science and mathematics. University of Novi Sad; 2008.
[3] Božanić DI, Pamučar DS. Evaluation of the bridge location for water obstacles crossing over by *fuzzy* logics. Vojnotehnički glasnik 2010;58(1):129–45.
[4] Kozarević S, Puška A. Corelation between implementation of supply chain, partner relationships and competitiveness. Econ Thought Practice 2015;24(2):579–96.
[5] Li S, Ragu-Nathan B, Ragu-Nathan TS, Subba Rao S. The impact of supply chain management practices on competitive advantage and organizational performance. Omega 2006;34(2):107–24. https://doi.org/10.1016/j.omega.2004.08.002.
[6] Ince H, Imamoglu SZ, Keskin H, Akgun A, Naci Efe M. The impact of ERP systems and supply chain management practices on firm performance: case of Turkish companies. Procedia Soc Behav Sci 2013;99:1124–33. https://doi.org/10.1016/j.sbspro.2013.10.586.
[7] Toyin AI. Supply Chain Management (SCM). Practices in Nigeria today: impact on SCM performance. Eur J Bus Soc Sci 2012;1(6):107–15.
[8] Sukati I, Hamid AB, Baharun R, Yusoff RM. The study of supply chain management strategy and practices on supply chain performance. Procedia Soc Behav Sci 2012;40:225–33. https://doi.org/10.1016/j.sbspro.2012.03.185.
[9] Jabbour ABLS, Filho AGA, Viana ABN, Jabbour CJC. Factors affecting the adoption of supply chain management practices, evidence from the Brazilian electro-electronic sector. IIMB Manag Rev 2011;23(4):208–22. https://doi.org/10.1016/j.iimb.2011.09.001.
[10] Miguel PLS, Brito LAL. Supply chain management measurement and its influence on operational performance. J Oper Supp Chain Manag 2011;4(2):56–70.
[11] Flynn BB, Huo B, Zhao X. The impact of supply chain integration on performance: a contingency and configuration approach. J Oper Manage 2010;28(1):58–71. https://doi.org/10.1016/j.jom.2009.06.001.
[12] Zhou H, Shou Y, Zhai X, Li L, Wood C, Wu X. Supply chain practice and information quality: a supply chain strategy study. Int J Prod Econ 2014;147:624–33. https://doi.org/10.1016/j.ijpe.2013.08.025.
[13] Mzoughi N, Bahri N, Ghachem MS. Impact of Supply Chain Management and ERP on organizational performance and competitive advantage: case of Tunisian companies. J Global Inf Technol Manag 2008;11(3):24–46. https://doi.org/10.1080/1097198X.2008.10856472.
[14] Li S, Rao S, Ragu-Nathan TS, Ragu-Nathan B. Development and validation of a measurement instrument for studying supply chain management practices. J Oper Manage 2005;23(6):618–41. https://doi.org/10.1016/j.jom.2005.01.002.
[15] Bayraktar E, Demirbag M, Lenny Koh SC, Tatoglu E, Zaim H. A causal analysis of the impact of information systems and supply chain management practices on operational performance: evidence from manufacturing SMEs in Turkey. Int J Prod Econ 2009;122:133–49. https://doi.org/10.1016/j.ijpe.2009.05.011.
[16] Barman D, Kushwaha GS, Des D. Impact of supply chain quality management on competitive advantage and organizational performance. Global Logist Manag 2008;9:171–85.
[17] Lai KH, Ngai EWT, Cheng TCE. An empirical study of supply chain performance in transport logistics. Int J Prod Econ 2004;87(3):321–31. https://doi.org/10.1016/j.ijpe.2003.08.002.
[18] Beamon MB. Measuring supply chain performance. Int J Oper Product Manag 1999;19(3):275–92. https://doi.org/10.1108/01443579910249714.
[19] Christopher M. Logistics and supply chain management. London: Prentice Hall & Financial Times; 2011. https://doi.org/10.1016/j.retrec.2012.10.006. 4th ed.
[20] Luetić A. Business intelligence and supply chain management PhD thesis Faculty of economics. University of Split; 2013.
[21] Cho DW, Lee YH, Ahn SH, Hwang MK. A framework for measuring the performance of service supply chain management. Comput Ind Eng 2012;62(3):801–18. https://doi.org/10.1016/j.cie.2011.11.014.
[22] Ganga GMD, Carpinetti LCR. A fuzzy logic approach to supply chain performance management. Int J Prod Econ 2011;134(1):177–87. https://doi.org/10.1016/j.ijpe.2011.06.011.
[23] Cai J, Liu X, Xiao Z, Liu J. Improving supply chain performance management: a systematic approach to analyzing iterative KPI accomplishment. Dec Support Syst 2009;46(2):512–21. https://doi.org/10.1016/j.dss.2008.09.004.
[24] Theeranuphattana A, Tang JCS. A conceptual model of performance measurement for supply chains: alternate considerations. J Manuf Technol Manag 2008;19(1):125–48. https://doi.org/10.1108/17410380810843480.
[25] Karsak EE, Dursun M. An integrated fuzzy MCDM approach for supplier evaluation and selection. Comput Ind Eng 2015;82:82–93. https://doi.org/10.1016/j.cie.2015.01.019.
[26] Moghaddam KS. Fuzzy multi-objective model for supplier selection and order allocation in reverse logistics systems under supply and demand uncertainty. Expert Syst Appl 2015;42:6237–54. https://doi.org/10.1016/j.eswa.2015.02.010.
[27] Orji JI, Wei S. An innovative integration of *fuzzy*-logic and systems dynamics in sustainable supplier selection: a case on manufacturing industry. Comput Ind Eng

2015;88:1–12. https://doi.org/10.1016/j.cie.2015.06.019.
[28] Chai J, Ngai EWT. Multi-perspective strategic supplier selection in uncertain environments. Int J Prod Econ 2015;166:215–25. https://doi.org/10.1016/j.ijpe.2014.09.035.
[29] Venkatesh VG, Rathi S, Patwa S. Analysis on supply chain risks in Indian apparel retail chains and proposal of risk prioritization model using Interpretive structural modeling. J Retail Consum Serv 2015;26:153–67. https://doi.org/10.1016/j.jretconser.2015.06.001.
[30] Mangla KS, Kumar P, Kumar Barua M. Prioritizing the responses to manage risks in green supply chain: An Indian plastic manufacturer perspective. Sustain Product Consump 2015;1:67–86. https://doi.org/10.1016/j.spc.2015.05.002.
[31] Rohmah DUM, Prima Dania WA, Atsari Dewi I. Risk measurement of supply chain organic rice product using fuzzy failure mode effect analysis in MUTOS Seloliman Trawas Mojokerto. Agric Agric Sci Proc 2015;3:108–13. https://doi.org/10.1016/j.aaspro.2015.01.022.
[32] Balaman ŞY, Selim H. A fuzzy multiobjective linear programming model for design and management of anaerobic digestion based bioenergy supply chains. Energy 2014;74:928–40. https://doi.org/10.1016/j.energy.2014.07.073.
[33] Balaman ŞY, Selim H. A decision model for cost effective design of biomass based green energy supply chains. Bioresour Technol 2015;191:97–109. https://doi.org/10.1016/j.biortech.2015.04.078.
[34] Zouggari A, Benyoucef L. Simulation based fuzzy TOPSIS approach for group multi-criteria supplier selection problem. Eng Appl Artif Intell 2012;25(3):507–19. https://doi.org/10.1016/j.engappai.2011.10.012.
[35] Chen CT, Lin CT, Huang SF. A fuzzy approach for supplier evaluation and selection in supply chain management. Int J Prod Econ 2006;102(2):289–301.
[36] Chatterjee K, Kar S. Multi-criteria analysis of supply chain risk management using interval valued fuzzy TOPSIS. OPSEARCH 2016;53(3):474–99. https://doi.org/10.1007/s12597-015-0241-6.
[37] Lee J, Cho H, Kim YS. Assessing business impacts of agility criterion and order allocation strategy in multi-criteria supplier selection. Expert Syst Appl 2015;42(3):1136–48. https://doi.org/10.1016/j.eswa.2014.08.041.
[38] Sheu JB. A hybrid neuro-*fuzzy* analytical approach to mode choice of global logistics management. Eur J Oper Res 2008;189(3):971–86. https://doi.org/10.1016/j.ejor.2006.06.082.
[39] Rostamzadeh R, Sabaghi M, Sofian S, Ismail Z. Hybrid GA for material routing optimization in supply chain. Appl Soft Comput 2015;26:107–22. https://doi.org/10.1016/j.asoc.2014.09.033.
[40] Kabra G, Ramesh A. Analyzing drivers and barriers of coordination in humanitarian supply chain management under fuzzy environment. Benchmarking 2015;22(4):559–87. https://doi.org/10.1108/BIJ-05-2014-0041.
[41] Bottani E, Rizzi A. A fuzzy TOPSIS methodology to support outsourcing of logistics services. Supply Chain Management 2006;11(4):294–308. https://doi.org/10.1108/13598540610671743.
[42] Kahraman C, Yasin Ateş N, Çevik S, Gülbay M. Erdoğan SA Hierarchical fuzzy TOPSIS model for selection among logistics information technologies. J Enterp Inf Manag 2007;20(2):143–68. https://doi.org/10.1108/17410390710725742.
[43] Ertugrul I, Tus A. Interactive fuzzy linear programming and an application sample at a textile firm. Fuzzy Optim Decis Mak 2007;6(1):29–49. https://doi.org/10.1007/s10700-006-0023-y.
[44] Bojadziev G, Bojadziev M. Fuzzy sets fuzzy logic applications. Singapore: World Scientific Publishing; 1998.
[45] Ashrafzadeh M, Rafiei FM, Isfahani NM, Zare Z. Application of fuzzy TOPSIS method for the selection of Warehouse location: a Case Study. Interdiscipl J Contemp Res Bus 2012;3(9):655–71.
[46] Pavkov I, Japundžić M. Role of fuzzy mathematics in economic decision making. Škola biznisa 2012;5(2):128–35.
[47] Panić G. Development of the purposed fuzzy logic system for application in XML document management systems PhD thesis Faculty for natural science and mathematics. University of Novi Sad; 2013.
[48] Chen CT. Extensions of the TOPSIS for group decision-making under fuzzy environment. Fuzzy Sets Syst 2000;114(1):1–9. https://doi.org/10.1016/j.ijpe.2005.03.009.
[49] Zimmermann HJ. Fuzzy set theory and its applications 2nd ed. Boston: Kluwer Academic Publishers and London: Dordrecht; 1991.
[50] Nang Idayu NZ, Lazim A. Evaluation of sustainable development indicators with fuzzy TOPSIS based on subjective and objective weights. IIUM Eng. J 2012;13(1):13–25.
[51] Chen SJ, Hwang CL. Fuzzy multiple attribute decision making methods and application. Lecture notes in economics and mathematical sciences. New York: Springer; 1992. https://doi.org/10.1007/978-3-642-46768-4.
[52] Wang YM, Elhang TMS. Fuzzy TOPSIS method based on alpha level sets with an application to risk management. Exp Syst Appl 2006;31(2):309–19. https://doi.org/10.1016/j.eswa.2005.09.040.
[53] Ertuğrul İ, Karakaşoğlu N. Comparison of fuzzy AHP and TOPSIS methods for facility location. Int J Adv Manuf Technol 2008;39(7):783–95. https://doi.org/10.1007/s00170-007-1249-8.
[54] Praščević Ž, Praščević N. One modification of fuzzy TOPSIS method. J Model Manag 2013;8(1):81–102. https://doi.org/10.1108/17465661311311996.
[55] Agarski B. Development of system for intelligent multicriterial estimation of environmental loading in the product life cycle estimation PhD thesis Faculty of technical sciences. University of Novi Sad; 2014.
[56] Mavi RK, Goh M, Mavi NK. Supplier selection with Shannon entropy and fuzzy TOPSIS in the context of supply chain risk management. Proc Soc Behav Sci 2016;235:216–25. https://doi.org/10.1016/j.sbspro.2016.11.017.
[57] Singh RK, Benyoucef L. A fuzzy TOPSIS based approach for e-sourcing. Eng Appl Artif Intell 2011;24(3):437–48. https://doi.org/10.1016/j.engappai.2010.09.006.
[58] Wang TC, Lee HD. Developing a fuzzy TOPSIS approach based on subjective weights and objective weights. Expert Syst Appl 2009;36(5):8980–5. https://doi.org/10.1016/j.eswa.2008.11.035.
[59] Milićević RM, Župac ŽG. Objective approach to the criterium weightening. Vojnotehnički glasnik 2012;60(1):39–56.
[60] Sundram VPK, Chandran VGR, Bhatti MA. Supply chain practices and performance: the indirect effects of supply chain integration. Benchmarking 2016;23(6):1445–71. https://doi.org/10.1108/BIJ-03-2015-0023.
[61] Chavez R, Fynes B, Gimenez C, Wiengarten F. Assessing the effect of industry clockspeed on the supply chain management practice-performance relationship. Supply Chain Manag 2012;17(3):235–48. https://doi.org/10.1108/13598541211227081.