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Prioritization of organizational capital measurement indicators using fuzzy AHP

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Abstract

Organizational capital is a sub-dimension of the intellectual capital which is the sum of all assets that make the creative ability of the organization possible. To control and manage such an important force, the companies must measure it first. This study aims at defining a methodology to improve the quality of prioritization of organizational capital measurement indicators under uncertain conditions. To do so, a methodology based on the extent fuzzy analytic hierarchy process (AHP) is applied. Within the model, three main attributes; deployment of the strategic values, investment to the technology and flexibility of the structure; their sub-attributes and 10 indicators are defined. To define the priority of each indicator, preferences of experts are gathered using a pair-wise comparison based questionnaire. The results of the study show that "deployment of the strategic values" is the most important attribute of the organizational capital.

Keywords: Organizational capital; Measurement indicators; Fuzzy sets; AHP; Prioritization

1. Introduction

Knowledge is a vital resource in any organization. It can be used to improve quality and customer satisfaction, and decrease cost in every meaning, if managed properly. Considering this management of knowledge, be it explicit or tacit, is a necessary prerequisite for the success in today's dynamic and changing environment [1].

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AS Wong and Aspinwall state in their paper: "As knowledge emerges as the primary strategic resource in the 21st century, many firms in the manufacturing and service sectors alike are beginning to introduce and implement Knowledge Management (KM). Organizations can certainly benefit from its application for enhanced decision support, efficiency and innovation, thus helping them to realize their strategic mission. However, KM is an emerging paradigm, and not many organizations have a clear idea of how to proceed with it." [2]

An OECD report on measuring KM in the business sector defines the KM concept as in the following: "KM covers any intentional and systematic process or practice of acquiring, capturing, sharing and using productive knowledge, wherever it resides, to enhance learning and performance in organizations. These investments in the creation of "organizational capability" aim at supporting – through various tools and methods – the identification, documentation, memorization and circulation of the cognitive resources, learning capacities and competencies that individuals and communities generate and use in their professional contexts. Practices, like formal mentoring, monetary, or non-monetary, reward for knowledge sharing and the allocation of resources to detect and capture external knowledge, are examples of knowledge management." [3]

The enormous changes that are reshaping the economy such as increased competition, rapidly evolving technology, more capricious customers, the growth of the internet and other factors are driving organizations to proactively manage their collective intellect [2] via KM tools. This collective intellect, or Intellectual Capital (IC) with other words, is the pursuit of effective use of knowledge (the finished product) as opposed to information (the raw material) [4].

Although the importance of knowledge as a strategic asset can be traced back several thousands of years, it was the ancient Egyptian and Greek civilizations that represented the first evidence of the codification of knowledge for the purposes of leveraging regional power with their implementations of national libraries and universities [5]. More recently, Machlup coined the term "intellectual capital" in 1962 and used it to emphasize the importance of general knowledge as essential to growth and development [5]. IC includes assets relating to employee knowledge and expertise, customer confidence in the company and its products, brands, franchises, information systems, administrative procedures, patents, trademarks and the efficiency of company business processes [6].

Today, IC is widely recognized as the critical source of true and sustainable competitive advantage [7]. Knowledge is the basis of IC and is therefore at the heart of organizational capabilities. Successfully utilizing that knowledge contributes to the progress of society [8].

IC was originally defined with three constructs (*i.e.* human capital, organizational capital and customer and relationship capital) [9], but some recent studies tend to rename customer and relational capital as relational capital only [10–12]. See Fig. 1 [12] for an illustrative definition of these constructs.

In this figure:

1. Human capital is the individual-level knowledge that each employee possesses [13].
2. Organizational capital is the sum of all assets that make the creative ability of the organization possible [11].
3. Relational capital is the sum of all assets that arrange and manage the firms' relations with the environment. The relational capital contains the relations with customers, shareholders, suppliers, and rivals, the state, the official institutions and society [11].

INTELLECTUAL CAPITAL

HUMAN CAPITAL	ORGANIZATIONAL CAPITAL	RELATIONAL CAPITAL
Individual-level knowledge	Mission-vision	Customers
Competence	Strategical values	Customer's loyalty
Leadership ability	Working systems	Market
Risk-taking and problem solving capabilities	Culture	Shareholders
	Management system	Suppliers
Education	Use of knowledge	Official institutions
Experience	Databases	Society

Fig. 1. Components of Intellectual Capital [12].

The organizational dimension, which is the focus of this paper, is defined in the intellectual capital as the organizational capital. The organizational capital is the sum of all assets that make the creative ability of the organization possible. The mission of the firm, its vision, basic values, strategies, working systems, and in-firm processes can be mentioned among these assets.

Organizational capital is one of the foundation stones of creating learning organizations. Even if the employees possess adequate or high capabilities, an organizational structure that is made up of weak rules and systems and which cannot turn these capabilities into a value, prevents the firm from having a high performance. On the contrary, a strong organizational capital structure creates a supporting environment to its workers and thus leads to workers' risk taking even after their failures. Besides, it leads to the decrease of the total cost and to the increase of the firm's profit and productivity. Therefore, the organizational capital is a vital structure for organizations and in an organizational level; it has a critical importance for the realization of measuring the intellectual capital [4].

Most of the time, if not always, companies have limited resources. Defining measurement indicators and their priorities for any important business activity helps companies by providing a guideline for their efforts towards success. By using these priorities, managers can decide in which activity they will invest first.

Many factors can be found in the literature to measure the organizational capital. Tangible assets such as the patents of the firm, copyrights, databases, computer programs and intangible assets such as the methods related to business management, company strategies, and the culture of the company are some frequently used factors among these [11]. The high investments of technology or the high number of computers and programs in a firm are not a feature, which adds an additional value to a firm by itself. In order for these to make a contribution to the company, the workers in the firm should have the abilities to use these systems to interpret the results, to make them knowledge and to use them in the relations [14]. As long as they are not in use, the existence of systems that possess and transmit knowledge, which is the foundation stone of the organizational capital, cannot effectively add value to the system. Therefore precise data concerning measurement indicators of organizational capital are not available or very hard to be extracted [11]. In addition, decision-makers prefer natural language expressions rather than sharp numerical values in assessing organizational capital parameters. So, organizational capital is an inherently fuzzy notion, which can be measured by the synthesis of its constituents. Fuzzy logic offers a systematic base in dealing with situations, which are ambiguous or not well defined. Indeed, the uncertainty in expressions such as "high level of the learning organizations" or "moderate creative ability of the organization" which are frequently encountered in the organizational capital literature is fuzziness.

Prioritization of IC measurement indicators is a multi-attribute decision problem which requires resolutions involved various stakeholders' interests. In order to assist management decision-making in selecting IC indicators for measurement and disclosure, Han and Han [15] suggest a model that identifies the criteria reflecting decision usefulness and expected risk factors. There has been no basis model for IC statements, nor bottom-line indicators of the value of IC before [15].

This study aims at defining a methodology to improve the quality of prioritization of organizational capital measurement indicators under uncertain conditions.

The paper is organized as follows: Section 2 defines the methodology of this research. Section 3 includes a hierarchical model for prioritization of OC measurement indicators. Section 4 includes a real-life numerical application. Finally, Section 5 presents the conclusions.

2. Methodology

In the literature, there is only one paper aiming at prioritizing human capital measurement indicators by using fuzzy AHP [16]. However, there is no fuzzy logic method aimed at prioritizing organizational capital measurement indicators. As a value-added to the literature on the topic, this paper aims at providing practitioners with a fuzzy point of view to the traditional intellectual capital analysis methods for dealing quantitatively with imprecision or uncertainty and at obtaining a fuzzy prioritization of organizational capital measurement indicators from this point of view that will close this gap considerably. Fuzzy multi-criteria methods such as fuzzy TOPSIS, fuzzy AHP and fuzzy outranking can solve such problems (see [17] for fuzzy multi-attribute decision making methods and their applications). Unlike many other decision theories (such as most inventory and scheduling models, linear programming, dynamic programming, etc.), MCDM methodologies are controversial and there is not a unique theory accepted by everyone in the field [18].

TOPSIS views a MADM problem with m alternatives as a geometric system with m points in the n-dimensional space. It was developed by Hwang and Yoon [19]. The method is based on the concept that the chosen alternative should have the shortest distance from the positive-ideal solution and the longest distance from the negative-ideal solution. TOPSIS defines an index called similarity (or relative closeness) to the positive-ideal solution and the remoteness from the negative-ideal solution. Then the method chooses an alternative with the maximum similarity to the positive-ideal solution [20].

The outranking decision aid methods compare all couples of actions. Instead of building complex utility functions, they determine which actions are being preferred to the others by systematically comparing them on each criterion. The comparisons between the actions lead to numerical results that show the concordance and/or the discordance between the actions, and then allow to select or to sort the actions that can be compared.

The most well known outranking methods are ELECTRE, ORESTE, and PROMETHEE [20–22].

AHP is developed by Saaty [23]. With this method, a complicated system is converted to a hierarchical system of elements. In each hierarchical level, pair-wise comparisons of the elements are made by using a nominal scale. These comparisons constitute a comparison matrix. To find the weight of each element, or the score of each alternative, the eigenvector of this matrix is calculated. At the end, the consistency of the pair-wise comparisons are calculated by using a consistency ratio. If it is below a predefined level, the comparisons are either revised by the decision-maker or excluded from the calculations.

In this paper, Fuzzy AHP will be preferred in the prioritization of organizational capital indicators since this method is the only one using a hierarchical structure among goal, attributes and alternatives. Usage of pair-wise comparisons is another asset of this method that lets the generation of more precise information about the preferences of decision-makers. Moreover, since the decision-makers are usually unable to explicit about their preferences due to the fuzzy nature of the decision process, this method helps them providing an ability of giving interval judgements instead of point judgements. Some recent examples of fuzzy AHP applications can be found in [24–28].

There are several fuzzy AHP methods explained in the literature. Table 1 gives a comparison of these methods, which have important differences in their theoretical structures. The comparison includes the advantages and disadvantages of each method. In this paper, the authors prefer Chang's extent analysis method [29,30] since the steps of this approach are relatively easier than the other fuzzy AHP approaches and similar to the conventional AHP.

In the following, the outlines of the extent analysis method on fuzzy AHP are given:

Let $X = \{x_1, x_2, \ldots, x_n\}$ be an object set, and $U = \{u_1, u_2, \ldots, u_m\}$ be a goal set. According to Chang's extent analysis [29,30], each object is taken and extent analysis for each goal, g_i, is performed respectively. Therefore, m extent analysis values for each object can be obtained, with the following signs:

$$M_{g_i}^1, M_{g_i}^2, \ldots, M_{g_i}^m, \quad i = 1, 2, \ldots, n \tag{1}$$

where all the $M_{g_i}^j$ $(j = 1, 2, \ldots, m)$ are triangular fuzzy numbers (TFNs) whose parameters are a, b, and c. They are the lowest possible value, the most possible value, and the largest possible value respectively. A TFN is represented as (a, b, c) as illustrated in Fig. 2.

The steps of Chang's extent analysis can be given as in the following:

Step 1. The value of fuzzy synthetic extent with respect to the ith object is defined as

$$S_i = \sum_{j=1}^{m} M_{g_i}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{g_i}^j \right]^{-1} \tag{2}$$

To obtain $\sum_{j=1}^{m} M_{g_i}^j$, perform the fuzzy addition operation of m extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} M_{g_i}^j = \left(\sum_{j=1}^{m} a_{ij},\ \sum_{j=1}^{m} b_{ij},\ \sum_{j=1}^{m} c_{ij} \right), \quad i = 1, 2, \ldots, n \tag{3}$$

Table 1
The comparison of different fuzzy AHP methods [31]

Sources	The main characteristics of the method	Advantages (A) and disadvantages (D)
Van Laarhoven and Pedrycz [32]	• Direct extension of Saaty's AHP method with triangular fuzzy numbers • Lootsma's logarithmic least square method is used to derive fuzzy weights and fuzzy performance scores	(A) The opinions of multiple decision-makers can be modeled in the reciprocal matrix (D) There is not always a solution to the linear equations (D) The computational requirement is tremendous, even for a small problem (D) It allows only triangular fuzzy numbers to be used
Buckley [33]	• Extension of Saaty's AHP method with trapezoidal fuzzy numbers • Uses the geometric mean method to derive fuzzy weights and performance scores	(A) It is easy to extend to the fuzzy case (A) It guarantees a unique solution to the reciprocal comparison matrix (D) The computational requirement is tremendous
Boender et al. [34]	• Modifies van Laarhoven and Pedrycz's method • Presents a more robust approach to the normalization of the local priorities	(A) The opinions of multiple decision-makers can be modeled (D) The computational requirement is tremendous
Chang [29]	• Synthetical degree values • Layer simple sequencing • Composite total sequencing	(A) The computational requirement is relatively low (A) It follows the steps of crisp AHP. It does not involve additional operations (D) It allows only triangular fuzzy numbers to be used
Cheng [35]	• Builds fuzzy standards • Represents performance scores by membership functions • Uses entropy concepts to calculate aggregate weights	(A) The computational requirement is not tremendous (D) Entropy is used when probability distribution is known. The method is based on both probability and possibility measures

and to obtain $\left[\sum_{i=1}^{n}\sum_{j=1}^{m}M_{g_i}^{j}\right]^{-1}$, perform the fuzzy addition operation of $M_{g_i}^{j}$ $(j = 1, 2, \ldots, m)$ values such that

$$\sum_{i=1}^{n}\sum_{j=1}^{m}M_{g_i}^{j} = \left(\sum_{i=1}^{n}\sum_{j=1}^{m}a_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{m}b_{ij},\ \sum_{i=1}^{n}\sum_{j=1}^{m}c_{ij}\right) \tag{4}$$

and then compute the inverse of the vector in Eq. (4) such that

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m}M_{g_i}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m}c_{ij}},\ \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m}b_{ij}},\ \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{m}a_{ij}}\right) \tag{5}$$

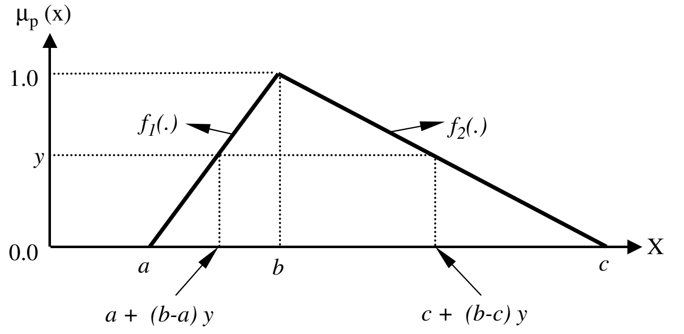

Fig. 2. A triangular fuzzy number, $\tilde{P} = (a, b, c)$.

Step 2. The degree of possibility of $M_2 = (a_2, b_2, c_2) \geqslant M_1 = (a_1, b_1, c_1)$ is defined as

$$V(M_2 \geqslant M_1) = \sup_{y \geqslant x} \left[\min(\mu_{M_1}(x), \mu_{M_2}(y)) \right]. \tag{6}$$

and can be equivalently expressed as follows:

$$V(M_2 \geqslant M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } b_2 \geqslant b_1 \\ 0, & \text{if } a_1 \geqslant c_2 \\ \dfrac{a_1 - c_2}{(b_2 - c_2) - (b_1 - a_1)}, & \text{otherwise} \end{cases} \tag{7}$$

where d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (see Fig. 3).

To compare M_1 and M_2, we need both the values of $V(M_1 \geqslant M_2)$ and $V(M_2 \geqslant M_1)$.

Step 3. The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers M_i $(i = 1, 2, \ldots, k)$ can be defined by

$$\begin{aligned} V(M \geqslant M_1, M_2, \ldots, M_k) &= V[(M \geqslant M_1) \text{ and } (M \geqslant M_2) \text{ and } \cdots \text{ and } (M \geqslant M_k)] \\ &= \min V(M \geqslant M_i), \quad i = 1, 2, 3, \ldots, k. \end{aligned} \tag{8}$$

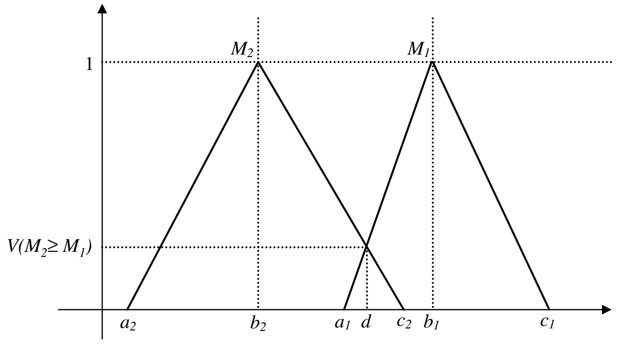

Fig. 3. The intersection between M_1 and M_2.

Table 2
Triangular fuzzy conversion scale

Linguistic scale	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Just equal	$(1, 1, 1)$	$(1, 1, 1)$
Equally important	$(1/2, 1, 3/2)$	$(2/3, 1, 2)$
Weakly more important	$(1, 3/2, 2)$	$(1/2, 2/3, 1)$
Strongly more important	$(3/2, 2, 5/2)$	$(2/5, 1/2, 2/3)$
Very strongly more important	$(2, 5/2, 3)$	$(1/3, 2/5, 1/2)$
Absolutely more important	$(5/2, 3, 7/2)$	$(2/7, 1/3, 2/5)$

Assume that

$$d'(A_i) = \min V(S_i \geqslant S_k) \tag{9}$$

For $k = 1, 2, \ldots, n$; $k \neq i$. Then the weight vector is given by

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^{\mathrm{T}} \tag{10}$$

where A_i ($i = 1, 2, \ldots, n$) are n elements.

Step 4. Via normalization, the normalized weight vectors are

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^{\mathrm{T}} \tag{11}$$

where W is a non-fuzzy number.

It is not possible to make mathematical operations directly on linguistic values. This is why, the linguistic scale must be converted into a fuzzy scale. In the literature about fuzzy AHP, one can find a variety of different fuzzy scales (see, for example, [28,36–38]). The triangular fuzzy conversion scale given in Table 2 is used in the evaluation model of this paper (adapted from [29]).

3. A hierarchical model for prioritization of OC measurement indicators

According to [4], organizational capital arises from processes and organizational value, reflecting the external and internal focuses of the company, plus renewal and development value for the future. A firm's organizational capital includes its norms and guidelines, databases, organizational routines and corporate culture [10].

This study aims at defining a methodology to improve the quality of prioritization of organizational capital measurement indicators under uncertain conditions. The method chosen, fuzzy AHP, requires a hierarchical structure to yield with a result. Therefore, the main attributes of the organizational capital are defined as deployment of the strategic values (DS), investments in the technology (IT) and flexibility of the organizational structure (FS). The first main attribute, DS, is characterized with two sub-attributes: Useableness of values in processes (UV) and fitness of values to daily working environment (FV). The second main attribute, IT, is characterized with three sub-attributes: Reliability (RE), ease of use (EU), and relevance (RV). The last main attribute, FS, is characterized with two sub-attributes: Supporting development (SD) and innovation (IN).

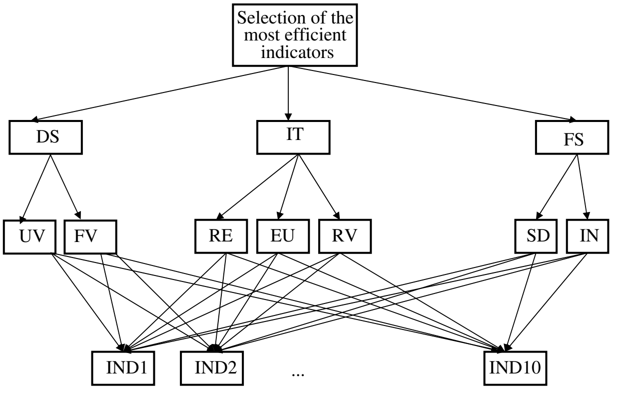

Fig. 4. Hierarchical structure of criteria.

The hierarchical structure defined above serves to the aim of prioritization of the OC measurement indicators. Ten indicators are selected [11], and defined as below:

IND1: Implementation rate of new ideas;
IND2: Quick access to information;
IND3: R&D investment rate per employee;
IND4: Access to all information without any limitation;
IND5: Increasing rate of revenue per employee;
IND6: Updating rate of the databases;
IND7: MIS contains all information;
IND8: Decreasing rate of cost per revenue;
IND9: Knowledge sharing rate;
IND10: Index of transaction time of the processes.

Fig. 4 illustrates the hierarchical structure explained above.

Independency of judgment at each level is one of the basic axioms of AHP. It means that a judgment at one level of hierarchy should be independent of the elements under it. This axiom must be taken into account since the decision-makers tend to look at the elements under the hierarchy while making evaluations. During the evaluation of this study, the experts were guided to end up with an independent judgment.

If there were interdependence among criteria of different layers, Analytical Network Process (ANP) would be used instead of AHP. ANP deals with such interdependence by obtaining the composite weights through the development of a "super matrix" [39].

4. A numerical application

To build the pair-wise comparison matrixes for the main and sub-attributes, and indicators, some academics and professionals are worked. A questionnaire (see Appendix A) is provided to get the evaluations. The results are calculated by taking the geometric mean of

Table 3
Pair-wise comparisons for main attributes

	DS	IT	FS
DS	(1, 1, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)
IT	(1/2, 2/3, 1)	(1, 1, 1)	(2/5, 1/2, 2/3)
FS	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 1, 1)

individual evaluations. For the first step of the analysis, the pair-wise comparison matrix for the main attributes is built (see Table 3).

For the first level (*i.e.* for main attributes), the values of fuzzy synthetic extents with respect to the main attributes are calculated as below (see Eq. (2)):

$$S_{\mathrm{DS}} = (2.5, 3.17, 4) \otimes (1/12.17, 1/9.83, 1/7.9) = (0.205, 0.322, 0.506)$$
$$S_{\mathrm{IT}} = (1.9, 2.17, 2.67) \otimes (1/12.17, 1/9.83, 1/7.9) = (0.156, 0.220, 0.338)$$
$$S_{\mathrm{FS}} = (3.5, 4.5, 5.5) \otimes (1/12.17, 1/9.83, 1/7.9) = (0.288, 0.458, 0.696)$$

The degrees of possibility are calculated as below (see Eq. (7)):

$$V(S_{\mathrm{DS}} \geqslant S_{\mathrm{IT}}) = 1, \quad V(S_{\mathrm{DS}} \leqslant S_{\mathrm{IT}}) = 0.566$$
$$V(S_{\mathrm{DS}} \geqslant S_{\mathrm{FS}}) = 0.616, \quad V(S_{\mathrm{DS}} \leqslant S_{\mathrm{FS}}) = 1$$
$$V(S_{\mathrm{IT}} \geqslant S_{\mathrm{FS}}) = 0.174, \quad V(S_{\mathrm{IT}} \leqslant S_{\mathrm{FS}}) = 1$$

For each pair-wise comparison, the minimum of the degrees of possibility is found as below: (see Eq. (8))

$$\mathrm{Min}\, V(S_{\mathrm{DS}} \geqslant S_i) = 0.616$$
$$\mathrm{Min}\, V(S_{\mathrm{IT}} \geqslant S_i) = 0.174$$
$$\mathrm{Min}\, V(S_{\mathrm{FS}} \geqslant S_i) = 1.000$$

These values yield the following weights vector:

$$W' = (0.616, 0.174, 1.000)^{\mathrm{T}}$$

Via normalization, the importance weights (*i.e.* eigenvalues) of the main attributes are calculated as follows:

$$W = (d(\mathrm{DS}), d(\mathrm{IT}), d(\mathrm{FS}))^{\mathrm{T}} = (0.345, 0.097, 0.558)$$

At the second level, the weights of the sub-attributes of each main attribute are calculated. As can be seen from Fig. 4, DS has two sub-attributes; UV, and FV. The pair-wise comparison for these two can be seen in Table 4.

The values of fuzzy synthetic extents with respect to DS are found as below:

$$(\mathrm{UV}, \mathrm{FV}) = (0.684, 0.316)$$

The second main attribute in the model, IT, has three sub-attributes; RE, EU, and RV. The pair-wise comparison for these three can be seen in Table 5.

Table 4
Pair-wise comparison for the sub-attributes of DS

	UV	FV
UV	(1,1,1)	(1,3/2,2)
FV	(1/2,2/3,1)	(1,1,1)

Table 5
Pair-wise comparison for the sub-attributes of IT

	RE	EU	RV
RE	(1,1,1)	(1,3/2,2)	(1,3/2,2)
EU	(1/2,2/3,1)	(1,1,1)	(1/2,2/3,1)
RV	(1/2,2/3,1)	(1,3/2,2)	(1,1,1)

Table 6
Pair-wise comparison for the sub-attributes of FS

	SD	IN
SD	(1,1,1)	(1/2,2/3,1)
IN	(1,3/2,2)	(1,1,1)

The values of fuzzy synthetic extents with respect to IT are found as below:

$$(\mathrm{RE}, \mathrm{EU}, \mathrm{RV}) = (0.467, 0.212, 0.322)$$

The third main attribute in the model, FS, has two sub-attributes; SD, and IN. The pair-wise comparison for these two can be seen in Table 6.

The values of fuzzy synthetic extents with respect to FS are found as below:

$$(\mathrm{SD}, \mathrm{IN}) = (0.320, 0.680)$$

For the third level, the pair-wise comparisons of indicators regarding to the sub-attributes are calculated. The first sub-attribute to be taken into account is UV. Table 7 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to UV are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.122738, 0.076566, 0.07811, 0.128534, 0.008074, 0.130324, 0.114358, 0.019649, 0.137914, 0.183732).

The second sub-attribute to be taken into account is FV. Table 8 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to FV are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.113086, 0.089316, 0.053684, 0.142309, 0.058197, 0.132163, 0.131783, 0.025734, 0.113823, 0.139904).

Table 7
Pair-wise comparison for the indicators regarding to the sub-attribute UV

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	(1, 1, 1)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 3/2, 2)	(2/3, 1, 2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/3, 1, 2)	(2/5, 1/2, 2/3)
Ind. 2	(2/5, 1/2, 2/3)	(1, 1, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)
Ind. 3	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1, 1, 1)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)
Ind. 4	(1/2, 2/3, 1)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 1, 1)	(3/2, 2, 5/2)	(2/3, 1, 2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1/2, 1, 3/2)	(1/2, 2/3, 1)
Ind. 5	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1/2, 1, 3/2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)
Ind. 6	(1/2, 1, 3/2)	(1, 3/2, 2)	(1, 3/2, 2)	(1/2, 1, 3/2)	(3/2, 2, 5/2)	(1, 1, 1)	(1, 3/2, 2)	(3/2, 2, 5/2)	(2/3, 1, 2)	(2/5, 1/2, 2/3)
Ind. 7	(1, 3/2, 2)	(1, 3/2, 2)	(1, 3/2, 2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)
Ind. 8	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/3, 1, 2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(2/5, 1/2, 2/3)	(1/3, 2/5, 1/2)
Ind. 9	(1/2, 1, 3/2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1/2, 1, 3/2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 1, 1)	(1/2, 2/3, 1)
Ind. 10	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(2, 5/2, 3)	(1, 3/2, 2)	(1, 1, 1)

Table 8
Pair-wise comparison for the indicators regarding to the sub-attribute FV

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	(1, 1, 1)	(1, 3/2, 2)	(3/2, 2, 5/2)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)
Ind. 2	(1/2, 2/3, 1)	(1, 1, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)
Ind. 3	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1, 1, 1)	(2/5, 1/2, 2/3)	(1/2, 1, 3/2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)
Ind. 4	(1/2, 1, 3/2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 1, 1)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 3/2, 2)	(1/2, 1, 3/2)
Ind. 5	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2/3, 1, 2)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)
Ind. 6	(1, 3/2, 2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(1, 1, 1)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 3/2, 2)
Ind. 7	(1, 3/2, 2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 1, 3/2)	(1, 1, 1)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1/2, 1, 3/2)
Ind. 8	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)
Ind. 9	(1, 3/2, 2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1, 3/2, 2)	(1, 1, 1)	(1/2, 2/3, 1)
Ind. 10	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 1, 1)

Table 9
Pair-wise comparison for the indicators regarding to the sub-attribute RE

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	(1, 1, 1)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)
Ind. 2	(3/2, 2, 5/2)	(1, 1, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(2, 5/2, 3)	(1, 3/2, 2)	(1/2, 1, 3/2)
Ind. 3	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1/3, 2/5, 1/2)	(1, 3/2, 2)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)
Ind. 4	(3/2, 2, 5/2)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 1, 1)	(2, 5/2, 3)	(2/3, 1, 2)	(1/2, 1, 3/2)	(2, 5/2, 3)	(1, 3/2, 2)	(1, 3/2, 2)
Ind. 5	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1, 1, 1)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1/2, 1, 3/2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)
Ind. 6	(3/2, 2, 5/2)	(1, 3/2, 2)	(2, 5/2, 3)	(1/2, 1, 3/2)	(2, 5/2, 3)	(1, 1, 1)	(1, 3/2, 2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)
Ind. 7	(3/2, 2, 5/2)	(1, 3/2, 2)	(2, 5/2, 3)	(2/3, 1, 2)	(2, 5/2, 3)	(1/2, 2/3, 1)	(1, 1, 1)	(2, 5/2, 3)	(1, 3/2, 2)	(3/2, 2, 5/2)
Ind. 8	(2/5, 1/2, 2/3)	(1/3, 2/5, 1/2)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(2/3, 1, 2)	(2/7, 1/3, 2/5)	(1/3, 2/5, 1/2)	(1, 1, 1)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)
Ind. 9	(1, 3/2, 2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(2, 5/2, 3)	(1, 1, 1)	(1/2, 2/3, 1)
Ind. 10	(1, 3/2, 2)	(2/3, 1, 2)	(1, 3/2, 2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(2, 5/2, 3)	(1, 3/2, 2)	(1, 1, 1)

Table 10
Pair-wise comparison for the indicators regarding to the sub-attribute EU

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	(1, 1, 1)	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(1/3, 2/5, 1/2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(1/2, 1, 3/2)
Ind. 2	(3/2, 2, 5/2)	(1, 1, 1)	(2, 5/2, 3)	(1/2, 2/3, 1)	(2, 5/2, 3)	(1, 3/2, 2)	(1, 3/2, 2)	(2, 5/2, 3)	(1/2, 1, 3/2)	(1, 3/2, 2)
Ind. 3	(2/5, 1/2, 2/3)	(1/3, 2/5, 1/2)	(1, 1, 1)	(1/3, 2/5, 1/2)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(1/3, 2/5, 1/2)	(1/2, 2/3, 1)
Ind. 4	(2, 5/2, 3)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 1, 1)	(2, 5/2, 3)	(1, 3/2, 2)	(1, 3/2, 2)	(5/2, 3, 7/2)	(1/2, 1, 3/2)	(3/2, 2, 5/2)
Ind. 5	(2/5, 1/2, 2/3)	(1/3, 2/5, 1/2)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1, 1, 1)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1, 3/2, 2)	(2/7, 1/3, 2/5)	(1/3, 2/5, 1/2)
Ind. 6	(1, 3/2, 2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2, 5/2, 3)	(1, 1, 1)	(1/2, 1, 3/2)	(2, 5/2, 3)	(1/2, 2/3, 1)	(1, 3/2, 2)
Ind. 7	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(2, 5/2, 3)	(2/3, 1, 2)	(1, 1, 1)	(2, 5/2, 3)	(1/2, 2/3, 1)	(1, 3/2, 2)
Ind. 8	(2/5, 1/2, 2/3)	(1/3, 2/5, 1/2)	(2/5, 1/2, 2/3)	(2/7, 1/3, 2/5)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1, 1, 1)	(2/7, 1/3, 2/5)	(2/5, 1/2, 2/3)
Ind. 9	(3/2, 2, 5/2)	(2/3, 1, 2)	(2, 5/2, 3)	(2/3, 1, 2)	(5/2, 3, 7/2)	(1, 3/2, 2)	(1, 3/2, 2)	(5/2, 3, 7/2)	(1, 1, 1)	(2/5, 1/2, 2/3)
Ind. 10	(2/3, 1, 2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(2, 5/2, 3)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(1, 1, 1)

Table 11
Pair-wise comparison for the indicators regarding to the sub-attribute RV

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	$(1,1,1)$	$(2,5/2,3)$	$(1/2,2/3,1)$	$(2,5/2,3)$	$(1/2,2/3,1)$	$(3/2,2,5/2)$	$(1,3/2,2)$	$(2/5,1/2,2/3)$	$(3/2,2,5/2)$	$(2,5/2,3)$
Ind. 2	$(1/3,2/5,1/2)$	$(1,1,1)$	$(1/3,2/5,1/2)$	$(1,3/2,2)$	$(1/3,2/5,1/2)$	$(1/2,1,3/2)$	$(1/2,2/3,1)$	$(2/7,1/3,2/5)$	$(2/3,1,2)$	$(1,3/2,2)$
Ind. 3	$(1,3/2,2)$	$(2,5/2,3)$	$(1,1,1)$	$(2,5/2,3)$	$(1/2,2/3,1)$	$(3/2,2,5/2)$	$(3/2,2,5/2)$	$(2/5,1/2,2/3)$	$(1,3/2,2)$	$(2,5/2,3)$
Ind. 4	$(1/3,2/5,1/2)$	$(1/2,2/3,1)$	$(1/3,2/5,1/2)$	$(1,1,1)$	$(1/3,2/5,1/2)$	$(2/3,1,2)$	$(1/2,2/3,1)$	$(2/7,1/3,2/5)$	$(2/5,1/2,2/3)$	$(1/2,1,3/2)$
Ind. 5	$(1,3/2,2)$	$(2,5/2,3)$	$(1,3/2,2)$	$(2,5/2,3)$	$(1,1,1)$	$(2,5/2,3)$	$(3/2,2,5/2)$	$(1/2,2/3,1)$	$(3/2,2,5/2)$	$(5/2,3,7/2)$
Ind. 6	$(2/5,1/2,2/3)$	$(2/3,1,2)$	$(2/5,1/2,2/3)$	$(1/2,1,3/2)$	$(1/3,2/5,1/2)$	$(1,1,1)$	$(1/2,2/3,1)$	$(2/7,1/3,2/5)$	$(1/2,2/3,1)$	$(1,3/2,2)$
Ind. 7	$(1/2,2/3,1)$	$(1,3/2,2)$	$(2/5,1/2,2/3)$	$(1,3/2,2)$	$(2/5,1/2,2/3)$	$(1,3/2,2)$	$(1,1,1)$	$(1/3,2/5,1/2)$	$(1/2,1,3/2)$	$(2,5/2,3)$
Ind. 8	$(3/2,2,5/2)$	$(5/2,3,7/2)$	$(3/2,2,5/2)$	$(5/2,3,7/2)$	$(1,3/2,2)$	$(5/2,3,7/2)$	$(2,5/2,3)$	$(1,1,1)$	$(3/2,2,5/2)$	$(5/2,3,7/2)$
Ind. 9	$(2/5,1/2,2/3)$	$(1/2,1,3/2)$	$(1/2,2/3,1)$	$(3/2,2,5/2)$	$(2/5,1/2,2/3)$	$(1,3/2,2)$	$(2/3,1,2)$	$(2/5,1/2,2/3)$	$(1,1,1)$	$(3/2,2,5/2)$
Ind. 10	$(1/3,2/5,1/2)$	$(1/2,2/3,1)$	$(1/3,2/5,1/2)$	$(2/3,1,2)$	$(2/7,1/3,2/5)$	$(1/2,2/3,1)$	$(1/3,2/5,1/2)$	$(2/7,1/3,2/5)$	$(2/5,1/2,2/3)$	$(1,1,1)$

Table 12
Pair-wise comparison for the indicators regarding to the sub-attribute SD

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	(1, 1, 1)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 3/2, 2)	(1/2, 1, 3/2)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 3/2, 2)	(1/2, 2/3, 1)
Ind. 2	(2/5, 1/2, 2/3)	(1, 1, 1)	(1/2, 2/3, 1)	(2/3, 1, 2)	(2/5, 1/2, 2/3)	(2/3, 1, 2)	(2/3, 1, 2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)
Ind. 3	(1/2, 2/3, 1)	(1, 3/2, 2)	(1, 1, 1)	(1, 3/2, 2)	(1/2, 1, 3/2)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1/2, 1, 3/2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)
Ind. 4	(1/2, 2/3, 1)	(1/2, 1, 3/2)	(1/2, 2/3, 1)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/3, 1, 2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(1/3, 2/5, 1/2)
Ind. 5	(2/3, 1, 2)	(3/2, 2, 5/2)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1, 1, 1)	(1, 3/2, 2)	(3/2, 2, 5/2)	(1/2, 1, 3/2)	(3/2, 2, 5/2)	(1/2, 2/3, 1)
Ind. 6	(1/2, 2/3, 1)	(1/2, 1, 3/2)	(1/2, 2/3, 1)	(1/2, 1, 3/2)	(1/2, 2/3, 1)	(1, 1, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/5, 1/2, 2/3)
Ind. 7	(1/2, 2/3, 1)	(1/2, 1, 3/2)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1, 1, 1)	(1/2, 2/3, 1)	(1/2, 1, 3/2)	(2/5, 1/2, 2/3)
Ind. 8	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(2/3, 1, 2)	(3/2, 2, 5/2)	(2/3, 1, 2)	(1, 3/2, 2)	(1, 3/2, 2)	(1, 1, 1)	(3/2, 2, 5/2)	(1/2, 2/3, 1)
Ind. 9	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(2/3, 1, 2)	(2/5, 1/2, 2/3)	(1, 1, 1)	(1/3, 2/5, 1/2)
Ind. 10	(1, 3/2, 2)	(2, 5/2, 3)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 3/2, 2)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 1, 1)

Table 13
Pair-wise comparison for the indicators regarding to the sub-attribute IN

	Ind. 1	Ind. 2	Ind. 3	Ind. 4	Ind. 5	Ind. 6	Ind. 7	Ind. 8	Ind. 9	Ind. 10
Ind. 1	(1, 1, 1)	(2, 5/2, 3)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(2, 5/2, 3)	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(1, 3/2, 2)
Ind. 2	(1/3, 2/5, 1/2)	(1, 1, 1)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)	(1, 3/2, 2)	(2/5, 1/2, 2/3)	(1/2, 2/3, 1)
Ind. 3	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(1, 1, 1)	(1, 3/2, 2)	(2, 5/2, 3)	(3/2, 2, 5/2)	(1, 3/2, 2)	(2, 5/2, 3)	(1/2, 1, 3/2)	(1, 3/2, 2)
Ind. 4	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(1/2, 2/3, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(1/2, 1, 3/2)	(1/2, 1, 3/2)	(2, 5/2, 3)	(1/2, 2/3, 1)	(3/2, 2, 5/2)
Ind. 5	(1/3, 2/5, 1/2)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(2/5, 1/2, 2/3)	(1, 1, 1)	(2/5, 1/2, 2/3)	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(1/3, 2/5, 1/2)	(2/5, 1/2, 2/3)
Ind. 6	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(2/3, 1, 2)	(3/2, 2, 5/2)	(1, 1, 1)	(1/2, 1, 3/2)	(2, 5/2, 3)	(1/2, 2/3, 1)	(1, 3/2, 2)
Ind. 7	(2/5, 1/2, 2/3)	(1, 3/2, 2)	(1/2, 2/3, 1)	(2/3, 1, 2)	(3/2, 2, 5/2)	(2/3, 1, 2)	(1, 1, 1)	(2, 5/2, 3)	(1/2, 2/3, 1)	(1, 3/2, 2)
Ind. 8	(2/7, 1/3, 2/5)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1/2, 2/3, 1)	(1/3, 2/5, 1/2)	(1/3, 2/5, 1/2)	(1, 1, 1)	(1/3, 2/5, 1/2)	(2/5, 1/2, 2/3)
Ind. 9	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(2/3, 1, 2)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 3/2, 2)	(1, 3/2, 2)	(2, 5/2, 3)	(1, 1, 1)	(3/2, 2, 5/2)
Ind. 10	(1/2, 2/3, 1)	(1, 3/2, 2)	(1/2, 2/3, 1)	(2/5, 1/2, 2/3)	(3/2, 2, 5/2)	(1/2, 2/3, 1)	(1/2, 2/3, 1)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)	(1, 1, 1)

Table 14
Priority weights of main and sub-attributes, and indicators

	DS 0.344645662		IT 0.096988434			FS 0.558365904		Weights
	UV 0.684211	FV 0.315789	RE 0.466523	EU 0.21163	RV 0.321848	SD 0.315789	IN 0.684211	
Ind. 1	0.122738	0.113086	0.063791	0.078642	0.167738	0.132275	0.216028	0.156842
Ind. 2	0.076566	0.089316	0.137589	0.161791	0.006464	0.057982	0.028529	0.058647
Ind. 3	0.07811	0.053684	0.030829	0.024112	0.182739	0.123138	0.157665	0.113803
Ind. 4	0.128534	0.142309	0.173309	0.185463	0	0.058709	0.119899	0.113605
Ind. 5	0.008074	0.058197	0	0	0.22302	0.139835	0	0.039856
Ind. 6	0.130324	0.132163	0.192902	0.131082	0	0.076346	0.119961	0.115826
Ind. 7	0.114358	0.131783	0.174788	0.138709	0.071391	0.055574	0.120076	0.109967
Ind. 8	0.019649	0.025734	0	0	0.276315	0.1316	0	0.039264
Ind. 9	0.137914	0.113823	0.104762	0.166405	0.072332	0.047937	0.165717	0.127086
Ind. 10	0.183732	0.139904	0.122031	0.113795	0	0.176603	0.072126	0.125104

The third sub-attribute to be taken into account is RE. Table 9 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to RE are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.063791, 0.137589, 0.030829, 0.173309, 0, 0.192902, 0.174788, 0, 0.104762, 0.122031).

The fourth sub-attribute to be taken into account is EU. Table 10 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to EU are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.078642, 0.161791, 0.024112, 0.185463, 0, 0.131082, 0.138709, 0, 0.166405, 0.113795).

The fifth sub-attribute to be taken into account is RV. Table 11 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to RV are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.167738, 0.006464, 0.182739, 0, 0.223020, 0, 0.071391, 0.276315, 0.072332, 0).

The sixth sub-attribute to be taken into account is SD. Table 12 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to SD are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.132275, 0.057982, 0.123138, 0.058709, 0.139835, 0.076346, 0.055574, 0.131600, 0.047937, 0.176603).

The seventh sub-attribute to be taken into account is IN. Table 13 shows the comparisons for that sub-attribute.

The values of fuzzy synthetic extents with respect to IN are found as below:

(Ind. 1, Ind. 2, Ind. 3, Ind. 4, Ind. 5, Ind. 6, Ind. 7, Ind. 8, Ind. 9, Ind. 10) = (0.216028, 0.028529, 0.157665, 0.119899, 0, 0.119961, 0.120076, 0, 0.165717, 0.072126).

In the last stage of the analysis, overall priority weights of the indicators are calculated as

(IND1, IND2, IND3, IND4, IND5, IND6, IND7, IND8, IND9, IND10) = (0.157, 0.059, 0.114, 0.114, 0.040, 0.116, 0.110, 0.039, 0.127, 0.125).

All of the results are summarized in Table 14.

5. Conclusion

The new millennium started a new era that can be called "era of knowledge". Managers started to realize that the market value of their companies is not defined only by the tangible assets any more. This is why IC, which is the sum of intangible assets of the company, has been one of the most popular concepts of this new era. Organizational capital is one of the three dimensions of IC.

Defining measurement indicators and their priorities help companies by providing a guideline for their efforts towards success. By using these priorities, managers can define their roadmap in using their scarce resources in potential investments.

Since organizational capital is an intangible asset, the prioritization of its sub-dimensions could successfully be handled with AHP. In this paper, the authors proposed a Fuzzy AHP method to improve the quality of prioritization of organizational capital measurement indicators under uncertain conditions. To do so, a hierarchical model consisting of three main attributes, seven sub-attributes, and 10 indicators is built. The model is verbalized in a questionnaire form including pair-wise comparisons.

The results calculated shows that the indicator *Implementation rate of new ideas* is the most important indicator for organizational capital measurement. The companies must pay full attention to implement newly created ideas and encourage the knowledge creation process. The sequence of the rest of the indicators according to their importance weights is as follows: IND9-Knowledge sharing rate, IND10-Index of transaction time of the processes, IND6-Updating rate of the databases, IND3-R&D investment rate per employee, IND4-Access to all information without any limitation, IND7-MIS contains all information, IND2-Quick access to information, IND5-Increasing rate of revenue per employee, IND8-Decreasing rate of cost per revenue. The weights calculated can help companies in self-assessments, and constitute a basis for benchmarking.

For further research, other fuzzy multi-criteria evaluation methods like fuzzy TOPSIS or fuzzy outranking methods can be used and the obtained results can be compared with the ones found in this paper.

Appendix A. Questionnaire forms used to facilitate comparisons of main and sub-attributes

QUESTIONNAIRE

Read the following questions and put check marks on the pairwise comparison matrices. If an attribute on the left is more important than the one matching on the right, put your check mark to the left of the importance " *Equal*" under the importance level you prefer. If an attribute on the left is less important than the one matching on the right, put your check mark to the right of the importance '*Equal*' under the importance level you prefer.

QUESTIONS

With respect to the overall goal "*prioritization of the organizational capital indicators*",
Q1. How important is *deployment of the strategic values (DS)* when it is compared with *investment in technology (IT)?*
Q2. How important is *deployment of the strategic values (DS)* when it is compared with *flexibility of the organizational structure (FS)?*
Q3. How important is *investment in technology (IT)* when it is compared with *flexibility of the organizational structure (FS)?*

With respect to: the overall goal		Importance (or preference) of one main-attribute over another											
Questions	Attributes	Absolutely More Important	Very Strongly More Important	Strongly More Important	Weakly More Important	Equally Important	Just Equal	Equally Important	Weakly More Important	Strongly More Important	Very Strongly More Important	Absolutely More Important	Attributes
Q1	DS			√									IT
Q2	DS								√				FS
Q3	IT									√			FS

With respect to the main attribute "deployment of the strategic values (DS)",
Q4. How important is *useableness of values in processes(UV)* when it is compared with *fitness of values to daily working environment (FV)?*

With respect to: Deployment of the str. values	Importance (or preference) of one sub-attribute over another

Questions	Sub-attributes	Absolutely More Important	Very Strongly More Important	Strongly More Important	Weakly More Important	Equally Important	Just Equal	Equally Important	Weakly More Important	Strongly More Important	Very Strongly More Important	Absolutely More Important	Sub-attributes
Q4	UV				√								FV

With respect to the sub-attribute *investment in technology (IT);*
Q5. How important is *reliability (RE)* when it is compared with *easy of usage (EU)?*
Q6. How important is *reliability (RE)* when it is compared with *relevance (RV) ?*
Q7. How important is *easy of usage (EU)* when it is compared with *relevance (RV)?*

With respect to: Inv. In Tech.		Importance (or preference) of one alternative over another											
Questions	Alternatives	Absolutely More Important	Very Strongly More Important	Strongly More Important	Weakly More Important	Equally Important	Just Equal	Equally Important	Weakly More Important	Strongly More Important	Very Strongly More Important	Absolutely More Important	Alternatives
Q5	RE				√								EU
Q6	RE				√								RV
Q7	EU								√				RV

With respect to the main attribute "*flexibility of the organizational structure (FS)*",

Q8. How important is *supporting development (SD)* when it is compared with *innovation (IN)?*

With respect to: Flex. of org. structure		Importance (or preference) of one sub-attribute over another											
Questions	Sub-attributes	Absolutely More Important	Very Strongly More Important	Strongly More Important	Weakly More Important	Equally Important	Just Equal	Equally Important	Weakly More Important	Strongly More Important	Very Strongly More Important	Absolutely More Important	Sub-attributes
Q8	SD								√				IN

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