Comparing fuzzy AHP and fuzzy TOPSIS for evaluation of business intelligence vendors

Alireza Soloukdar[a*] and Seyedeh Akram Parpanchi[b]

[a]*Department of Industrial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran*
[b]*Department of Information Technology Management, Electronic Branch, Islamic Azad University, Tehran, Iran*

C H R O N I C L E	A B S T R A C T
	The main objective of this study is to identify the most important criteria and indicators in selection of business intelligence vendors, and ranking the vendors of such tools using Fuzzy Analytical hierarchy Process (FAHP) and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS), to compare results of these two methods and to provide appropriate solutions for the sample company, namely National Iranian Oil Company (NIOC). Spearman's rank correlation test was used for comparing the methods and determining their correlation. A strong positive correlation was observed between the ranks of business intelligence tools at the significance level of 0.05 in both methods. The results of the ranking by means of FAHP method show that IBM Company was the best one, followed by Oracle, SAS, QlikTech, SAP and Microsoft. However, based on the FTOPSIS method, Oracle was the leading company, followed by IBM, SAS and SAP and finally Microsoft.

1. Introduction

Business intelligence (BI) is an IT approach that assists many organizations in making accurate and timely decisions, improving supervision process to provide better support for their own operational activities, strategic and tactical planning, and forecasting and analyzing market segments. Using business intelligence solutions, organizations are able to have better access to information and use analytical methods for optimizing their business performance. Substantial increase in value of business, better decision-making and high returns on investment are only some of the arguments offered by its vendors. Because of such promises, many organizations have invested in business intelligence. Such an increase of value of business has been achieved in numerous business organizations, and business intelligence has produced satisfactory results (Turban & Turban, 2007).

The term "business intelligence" has become increasingly popular in the recent decade and given various definitions has been offered recently for business intelligence applications, so that it can be said that its definition is an endless and non-conclusive debate and varies from author to author. The current

picture of business intelligence is a multifaceted concept, which may include processes, techniques and tools to support better and faster decision-making (Pirttimak & Hannula, 2003). In many cases, some firms are using business intelligence tools or solutions, but under various names such as management information systems (MIS), decision support systems (DSS), executive information systems (EIS), and so on (Pagels-Fick, 2000). Typically, the same organizations unintentionally call a small portion of some systems as "business intelligence systems", such as customer relationship management (CRM) and knowledge management that focuse exclusively on clients and knowledge, while a business intelligence system mainly deals with the data (Solberg Soilen, 2008).

Users of business intelligence systems often tend to consider their commercial aspects rather than their technological ones (Bräutigam et al., 2006). This person, business intelligence user, is often responsible for selecting or experiencing the process of selection of the best business intelligence system for his/her organization to invest in. Selection of business intelligence systems is a sophisticated and time-consuming process involving many resources and sectors. Making decision about which business intelligence solution to be implemented and which business intelligence vendor to be used is very difficult and requires a thorough investigation and comparison of the alternatives. A proper distinction between offered arguments and the arguments provided by vendors cannot be easily made without a firm basis for reasoning. Previous studies have shown that measuring the direct benefits from investment in IT is a difficult task (Falk & Olve, 1996). Due to the problematic nature of appraisal of the investment in IT sector, it can be a remarkable, interesting and different approach in evaluating and assessment of the vendors of different business intelligence tools and systems. Nevertheless, current organizational systems are the foundations of each organization. Design and implementation of business intelligence has been considered as an umbrella concept for developing a decision support environment for managing organizational systems. The increasing tendency towards using smart tools in business systems has intensified the necessity for evaluating and ranking business intelligence tools. As far as we are aware, little research has been devoted concerning ranking and assessment of such tools. The results of the current research can be significantly helpful for managers and decision makers in organizations for implementing business intelligence solutions. We expect that this research help managers and organizations for proper understanding and selection of business intelligence tools and effective implementation of business intelligence systems.

The main objective of this study is to identify key indicators and criteria for selecting business intelligence tools and vendors, evaluating and ranking business intelligence tools using fuzzy multi-criteria decision-making methods, and finally recommending appropriate mechanisms for the sample company, namely National Iranian Oil Company.

2. Materials and methods

2.1. Research method

The present study is an applied one in terms of objective, and descriptive in terms of method due to the fact that the relationship between variables and indicators (factors) have not been addressed while the status quo of National Iranian Oil Company has been focused on; meanwhile, since the data has been obtained from the staff of the NIOC, it is a survey research.

The detailed methodology includes a descriptive and inferential method for identification of the effective criteria and sub-criteria, an applied method in terms of ranking and prioritizing the vendors, and a correlational research method for studying the relationship and the significant differences between the two methods. Accordingly, the identification of effective criteria was conducted using descriptive statistics methods and then Student's t-test method was applied to test the hypotheses; then, fuzzy analytical hierarchy process (FAHP) and fuzzy TOPSIS (FTOPSIS) method were used in proportion to the research objectives, the significant difference and research hypotheses. Ultimately, Spearman's correlation test was used for studying the significance of the relationship between the two methods.

2.1.1. Fuzzy analytic hierarchy process (FAHP)

Zadeh (1965) proposed fuzzy set theory for the uncertainty introduced by ambiguity. The most important feature of the fuzzy set theory is its capacity to show vague and uncertain data. Leung and Cao (2000) argued that one of the reasons for low accuracy of traditional AHP method in obtaining the individuals' opinions is because the person is asked to assign a definite value to the pairwise comparisons based on his/her understanding of the phenomenon, meanwhile, an understanding of the phenomenon cannot be expressed as a crisp score and an interval of the numbers can better reflect the understanding of a person regarding the importance of a phenomenon compared with other phenomena than crisp numbers do. Thus, fuzzy AHP can better simulate the decision-making process of human mind than traditional AHP can. Laarhoven and Pedrcyz (1983) for the first time used fuzzy AHP method by using triangular fuzzy numbers. In 1996, Chang introduced a new approach for fuzzy AHP analysis. So far, many researchers have used fuzzy AHP method in their researches, for example for determining the importance of customer requirements (Chan et al., 2012), for vendor selection (Shaw et al., 2012), selection of ERP consultants (Vayvay et al., 2012), risk assessment (Wang et al., 2012), performance appraisal of business intelligence systems (Rezaie et al., 2011) and numerous other issues. The steps required for this research include:

Step 1: Obtaining hierarchical structure by finding the criteria, sub-criteria and alternatives

As previously mentioned, the criteria and sub-criteria affecting the ranking of business intelligence tools, including three main criteria, 19 sub-criteria are 6 alternatives, have been obtained by review of the literature and obtaining the experts' opinions regarding this problem.

Step 2: Collecting experts' opinions in form of fuzzy numbers and building fuzzy pairwise comparison matrices and aggregating the experts' opinions

At this stage, to collect experts' opinions, tangible and common expressions in the fuzzy AHP pairwise comparisons questionnaires have been used rather than deterministic values common in traditional AHP. The scale used in this research is a scale of 1-9 triangular fuzzy numbers proposed by Tesfamariam and Sadiq (2006) based on Saaty scale. After collecting the responses from experts in a 9-point scale and in form of some verbal expressions, the responses should be transferred to a scale capable of analyzing the responses, since it is impossible to perform mathematical operations on qualitative variable expressions. The variable expressions, thus, must be converted to fuzzy scales. The triangular fuzzy scales contribute to better decision-making process (Kaufmann, & Gupta, 1988). Table 1 shows the fuzzy numbers corresponding to verbal scales derived from the study by Tesfamariam and Sadiq (2006).

Table 1
Fuzzy numbers corresponding to verbal scales

Verbal variable	Fuzzy number	Scale of the corresponding number
Equal importance	$\tilde{1}$	(1, 1, 1)
Intermediate values between two adjacent judgments	$\tilde{2}$	(1, 2, 3)
Weak importance	$\tilde{3}$	(2, 3, 4)
Intermediate values between two adjacent judgments	$\tilde{4}$	(3, 4, 5)
Strong importance	$\tilde{5}$	(4, 5, 6)
Intermediate values between two adjacent judgments	$\tilde{6}$	(5, 6, 7)
Extreme importance	$\tilde{7}$	(6, 7, 8)
Intermediate values between two adjacent judgments	$\tilde{8}$	(7, 8, 9)
Absolute more importance	$\tilde{9}$	(8, 9, 9)

The triangular fuzzy number is shown in Fig. 1 and Eq. (1). A triangular fuzzy number is shown as (l, m, u). Parameters l, m, and u represent the lowest possible value, the most probable value and the highest possible value, respectively.

$$\tilde{a}_{ij}^{k} = (l_{ij}, m_{ij}, u_{ij}) \quad ; l_{ij} \leq m_{ij} \leq u_{ij}, l_{ij}, m_{ij}, u_{ij} \in [1/9, 9] \tag{1}$$
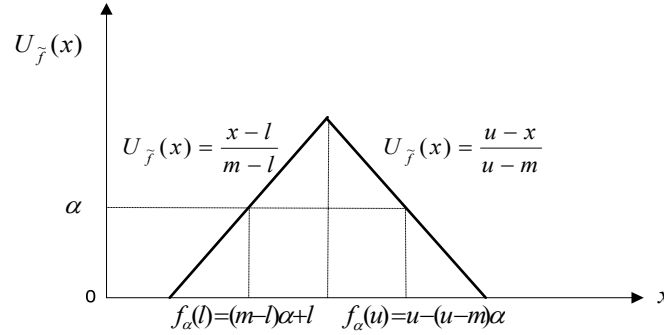
Fig. 1. Triangular fuzzy number

Each triangular fuzzy number has a membership function according to what is stated in Eq. (2). Fuzzy pairwise comparison matrix has been shown in Eq. (3).

$$U(x) = \begin{cases} \dfrac{x-l}{m-l} & l \leq x \leq m \\ \dfrac{u-x}{u-m} & m \leq x \leq u \\ 0 & \text{Otherwise} \end{cases} \tag{2}$$

where: $\tilde{A}^{k}$ is the decision matrix of kth decision maker, and $\tilde{a}_{ij}^{k}$ is the fuzzy assessment of kth decision maker regarding the pairwise comparison of i and j criteria, and $\tilde{a}_{ij} = (l_{ij}^{k}, m_{ij}^{k}, u_{ij}^{k})$ and also

$$\tilde{a}_{ij}^{k} = (1,1,1): \forall i = j; \; \tilde{a}_{ij}^{k} = \frac{1}{\tilde{a}_{ij}^{k}} : \forall i \neq j$$
$$\tilde{A}^{k} = [\tilde{a}_{ij}]^{k} \tag{3}$$

Basic algebraic operations for two positive triangular fuzzy numbers $\tilde{A}$ and $\tilde{B}$ can be viewed as summarized in Table 2.

Table 2

Basic algebraic operations for two positive triangular fuzzy numbers $\tilde{A}$ and $\tilde{B}$

Operator	Equation	Result
Summation	A+B	$(l_1+l_2, m_1+m_2, u_1+u_2)$
Subtraction	A-B	$(l_1-u_2, m_1-m_2, u_1-l_2)$
Multiplication	A×B	$(l_1 \times l_2, m_1 \times m_2, u_1 \times u_2)$
Division	A/B	$(l_1/u_2, m_1/m_2, u_1/l_2)$

A=(l_1, m_1, u_1);B= (l_2, m_2, u_2)

After building the matrix of pairwise comparisons for each expert, the experts' opinions should be aggregated. In this study, the arithmetic mean calculation method has been used for crisp opinions of the experts (according to Eq. (4)) to obtain the aggregation of opinions of individuals and preparing the final matrices of pairwise comparisons.

$$a^*_{ij} = \sqrt[k]{\left(a^{*1}_{ij} \times a^{*2}_{ij} \times ... \times a^{*k}_{ij} \right)} \tag{4}$$

$$A^*_{ij} = [a^*_{ij}] \tag{5}$$

Step 3: Calculating the consistency ratio

Studying the consistency of fuzzy pairwise comparisons matrices is not as easy as that of crisp matrices. To solve this problem Csutora and Buckley (2001) showed in their paper that if $\tilde{A} = [\tilde{a}_{ij}]$ is the matrix of fuzzy pairwise comparisons with fuzzy triangular fuzzy numbers $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$, the only thing that must be determined is the consistency of $A = [m_{ij}]$ matrix. If A will be consistent, then $\tilde{A}$ will be consistent too. However, when the decision matrix is not fully consistent, consistency index of matrix of pairwise comparisons will be determined after obtaining the intermediate values of the matrices and calculation of the largest eigenvalue of λ_{max} using Eq. (6):

$$C.I = (\lambda_{max} - n)/(n-1) \tag{6}$$

If the concerning matrix will be fully consistent, then $\lambda_{max} = n$. The more the matrix will be close to the full consistency; the closer will be the value of λ_{max} to n, i.e. number of factors that are compared. The consistency index represents the consistency of decision-making matrix. As it can be seen, the index is associated with n. For making the index independent of n, it should be divided by another index called "random index" (R.I). The latter index is calculated from the mean consistency ratio of the randomly generated decision-making matrices. Table 3 shows RI values for different values. The new index is called consistency ratio (CR) and is included in Eq. (7) (Saaty, 1990).

$$C.R = C.I/R.I \tag{7}$$

Table 3
Random index values for each dimension of decision matrix (n)

n	3	4	5	6	7	8	9	10	11	12	13	14	15
$R.I$	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Step 4: Calculation of crisp matrix of aggregated experts' opinions using CFCS method

After being ensured of the consistency of the opinions, matrix of pairwise comparisons must be converted from fuzzy scale to crisp scale, which is called defuzzification of fuzzy pairwise comparison matrix. Different methods have been proposed for defuzzification of fuzzy pairwise comparison matrix, here the approach proposed by Opricovic and Tzeng (2003) will be used for defuzzification of fuzzy answers of the experts using Eqs. (8-15). If $\tilde{A}_{ij}^k = (l_{ij}^k, m_{ij}^k, u_{ij}^k)$ will be the pairwise comparison matrix of the kth expert regarding the pairwise comparison between i and j criteria, then the steps of CFCS method are as follows:

1: Calculating the normalized matrix

$$xl_{ij}^k = (l_{ij}^k - \min l_{ij}^k)/\Delta_{min}^{max} \tag{8}$$

$$xm_{ij}^k = (m_{ij}^k - \min l_{ij}^k)/\Delta_{min}^{max} \tag{9}$$

$$xu_{ij}^{k} = (u_{ij}^{k} - \min l_{ij}^{k}) \big/ \Delta_{min}^{max} \tag{10}$$

Where,

$$\Delta_{min}^{max} = \max u_{ij}^{k} - \min l_{ij}^{k} \tag{11}$$

2: Calculating the normal left (ls) and right (us) values

$$xls_{ij}^{k} = xm_{ij}^{k} \big/ (1 + xm_{ij}^{k} - xl_{ij}^{k}) \tag{12}$$

$$xus_{ij}^{k} = xu_{ij}^{k} \big/ (1 + xu_{ij}^{k} - xm_{ij}^{k}) \tag{13}$$

3: Calculating the crisp normalized value

$$x_{ij}^{k} = [xls_{ij}^{k}(1 - xls_{ij}^{k}) + xus_{ij}^{k}] \big/ [1 - xls_{ij}^{k} + xus_{ij}^{k}] \tag{14}$$

4: Calculating the crisp values

$$a_{ij}^{*k} = \min l_{ij}^{k} + x_{ij}^{k} \Delta_{min}^{max} \tag{15}$$

Step 5: Calculating the final weights

To obtain the weights, calculating the geometric mean of row vector of crisp decision matrix introduced by Saaty (1980) has been used (shown in Eq. (16)).

$$w_i = \frac{(\prod_{j=1}^{n} a_{ij}^{*})^{1/n}}{\sum_{i=1}^{n} (\prod_{j=1}^{n} a_{ij}^{*})^{1/n}} \qquad i, j = 1, 2, ..., n \tag{16}$$

3. Fuzzy TOPSIS Method (FTOPSIS)

TOPSIS method was introduced for the first time by Hwang and Yoon (1981). In summary, in this approach the best choice is the closest one to the positive ideal point and yet farthest one from the negative ideal one. The data and inputs of the method are similar to those of the previously explained fuzzy AHP method, i.e. experts' opinions. In this method, experts determine the relative importance of the criteria or sub-criteria and then assess the performance of each alternative against each criterion. However, human's thought and expression of evaluations are accompanied with uncertainty, and this uncertainty has an impact on decision-making. To overcome this issue, fuzzy decision-making methods are used. In this case, the decision matrix elements, or the importance of criteria against alternatives and the importance of criteria (in our problem) are expressed in a fuzzy manner by means of fuzzy number. Fuzzy AHP methodology, like fuzzy TOPSIS method has been used in many cases by various researchers such as Krohling and Campanharo (2011) on the issue of oil spill incidents at sea, Torlak et al. (2011) for competitiveness of businesses in Turkey, and Liao and Kao (2011) for vendor selection problem, and Kelemenis et al. (2011), for selecting support managers. Fuzzy and verbal scales used to measure the importance of the criteria (here sub-criteria) and performance of alternatives, i.e. business intelligence software providers, against each criterion are given in Tables 4 and 5 (Wang & Elhag, 2006).

Table 4
Verbal scales for evaluation of importance of criteria

Verbal importance	Very High	High	Medium High	Medium	Low Medium	Very	Very Low
Code	VH	H	MH	M	ML	L	VL
Corresponding triangular fuzzy numbers	0.9, 1.0, 1.0	0.7, 0.9, 1.0	0.5, 0.7, 0.9	0.3, 0.5, 0.7	0.1, 0.3, 0.5	0, 0.1, 0.3	0, 0, 0.1

Table 5
Verbal scales for alternative performances against each sub-criterion

Verbal importance	Very good	Good	Medium good	Fair	Medium poor	Poor	Very Poor
Code	VG	G	MG	F	MP	P	VP
Corresponding triangular fuzzy numbers	9, 10, 10	7, 9, 10	5, 7, 9	3, 5, 7	1, 3, 5	0, 1, 3	0, 0, 1

Necessary steps for implementation of fuzzy TOPSIS method are as follows (Chen et al., 2006):

Step 1:

Suppose that we have *m* alternatives, *n* criteria and *k* decision makers, then, fuzzy multi-criteria decision-making problem can be expressed as the following matrix:

$$\tilde{D} = \begin{matrix} & \begin{matrix} X_1 & \cdots & X_j & \cdots & X_n \end{matrix} \\ \begin{matrix} A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{i1} & \cdots & \tilde{x}_{ij} & \cdots & \tilde{x}_{in} \\ \vdots & & \vdots & & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{bmatrix} \end{matrix} \qquad i = 1, 2, ..., m; \ j = 1, 2, ..., n \tag{17}$$

where, $A_1, A_2, ..., A_n$ are the alternatives that should be selected or ranked; $C_1, C_2, ..., C_n$ are the evaluation criteria or characteristics; $\tilde{x}_{ij}$ is the desirability of alternative A_i against criterion C_j determined by the *k*th expert. In order to aggregate fuzzy performance scores of $\tilde{x}_{ij}$ for *k* experts, arithmetic mean has been used according to Eq. (18):

$$\tilde{x}_{ij} = \frac{1}{k}(\tilde{x}_{ij}^1 + \tilde{x}_{ij}^2 + ... + \tilde{x}_{ij}^k), \tag{18}$$

where, $\tilde{x}_{ij}^k$ is the desirability of alternative against A_i against criterion C_j determined by the *k*th expert and $\tilde{x}_{ij}^k = (a_{ij}^k, b_{ij}^k, c_{ij}^k)$. Moreover, the mean of fuzzy importance of each sub-criterion will be determined in this step. The weights are shown as triangular fuzzy numbers and $\tilde{w}_j = (\overline{l}, \overline{m}, \overline{u})$ and each component of this number is the corresponding mean of (the first, second or third) opinions of the experts.

Step 2: Normalizing fuzzy decision matrix and calculating the weighted normalized fuzzy decision matrix

In this step, given that the raw data obtained from the removal of heterogeneous units and various decision-making scales should be normalized in multi-criteria decision-making problems, the linear normalization is used for this purpose. If $\tilde{R}$ is the normalized fuzzy decision matrix, then we have:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n}, \quad i = 1, 2, ..., m; \ j = 1, 2, ..., n \tag{19}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+} \right) \quad c_j^+ = \max_i c_{ij} \ j \in B \tag{20}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right) \quad a_j^- = \min_i a_{ij} \ j \in C \tag{21}$$

where, B and C are the set of positive and negative criteria respectively. Considering different weights for each sub-criterion, the weighted normalized decision matrix is calculated by multiplying the importance weights of the criteria by normalized fuzzy decision matrix. Weighted normalized decision matrix $\tilde{V}$ is defined as follows, where $\tilde{w}_j$ is the weight of the *j*th criterion:

$$\tilde{V} = [\tilde{v}_{ij}]_{m \times n}, \quad i=1,2,...,m; \ j=1,2,...,n \tag{22}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j$$

Step 3: Determining the positive and negative ideal solutions

The positive and negative ideal solutions are defined as follows:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+,...,\tilde{v}_n^+) \tag{23}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-,...,\tilde{v}_n^-)$$

where:

$$A^+ = \left\{ \left(\max_i v_{ij} \,|\, j \in J \right), \left(\min_i v_{ij} \,|\, j \in J' \right) | i = 1,2,...,m \right\} = \left\{ v_1^+, v_2^+,...,v_j^+,...,v_n^+ \right\} \tag{24}$$

$$A^- = \left\{ \left(\min_i v_{ij} \,|\, j \in J \right), \left(\max_i v_{ij} \,|\, j \in J' \right) | i = 1,2,...,m \right\} = \left\{ v_1^-, v_2^-,...,v_j^-,...,v_n^- \right\} \tag{25}$$

$J = \{ j = 1,2,...,n \}$:J related to negative criteria

$J' = \{ j = 1,2,...,n \}$: J related the positive criteria

Step 4: Calculating the distance of each alternative from the positive and negative ideal points

The distance between each alternative and the fuzzy positive ideal solution and fuzzy negative ideal solution are calculated as follows:

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad i=1,2,...,m; \ j=1,2,...,n \tag{26}$$

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

where, $d(\tilde{v}_a, \tilde{v}_b)$ represents a distance between the two fuzzy numbers, and d_i^+ represents the distance of alternative i from positive ideal point, while d_i^- represents distance of alternative i from negative ideal solution. If we have two triangular fuzzy numbers, $M(m_1, m_2, m_3)$, $N((n_1, n_2, n_3)$ then the fuzzy distance between two numbers is calculated as follows:

$$d(M,N) = \sqrt{\frac{1}{3}\left[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2 \right]} \tag{27}$$

Step 5: Calculating the closeness coefficient and ranking the alternatives

By determining the closeness coefficient, the final step will be taken for ranking all alternatives and decision makers can choose the best alternative among several alternatives. Closeness coefficient of each alternative is calculated as follows:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i=1,2,...,m \tag{28}$$

If CC_i index will be close to one, the alternative will be close to the positive ideal point and far from the negative ideal point. Thus, the larger the value of CC_i will be, the better performance A$_i$ will have.

2.2 Data Collection Methods

For understanding influencing factors and parameters on business intelligence tools and determining such tools, data collection was conducted using desk studies, while gathering the data concerning the statistical population was conducted using interviews and questionnaires. The questionnaires were prepared for identifying the factors and indicators of business intelligence tools (at the second level) and preparing the decision matrices (to be used in TOPSIS method), while the data collection was

conducted for AHP.

2.3 Statistical Population, Sampling and Sample Size

The statistical population includes the experts of the National Iranian Oil Company in the field of information technology. Considering the number of subjects included in the statistical population and in order to achieve more accurate results, census sampling technique was used. The data regarding the factors and parameters influencing business intelligence tools and selection of business intelligence tools was collected by review of literature. Meanwhile gathering the data concerning the statistical population was conducted using interviews and questionnaires. Census sampling method was used for identifying the criteria and indicators using the opinions of 30 IT experts in NIOC, while with the help of AHP and fuzzy TOPSIS questionnaires and the sampling technique, the opinions of seven business intelligence experts were obtained and used for evaluating and ranking the criteria, sub-criteria and the alternatives.

2.4 Data Analysis Methods and Tools

In this study, data analysis was conducted using arithmetic mean (descriptive statistics) in order for determining and identifying the influencing parameters and factors; fuzzy AHP and fuzzy TOPSIS methods were used for identifying and ranking business intelligence tools, and Spearman's rank correlation test was used for comparing the methods regarding the test of the hypotheses. The applications used in this analysis include SPSS, Excel, Expert Choice and Matlab. The used data analysis methods can be noted as follows:

1. Student's T-test as an inferential test for determining and identifying the effective factors and indicators.
2. Fuzzy AHP method for evaluating and prioritizing indicators related to the vendors of intelligence tools and solutions.
3. Fuzzy TOPSIS method for ranking the vendors of business intelligence tools and solutions based on the experts' opinions in NIOC.
4. Spearman's rank correlation test for evaluating and comparing the significance of the relationship between the two methods, i.e. fuzzy AHP and fuzzy TOPSIS methods.

2.5 Scope of Research

Thematic scope of this study is evaluating and ranking the criteria, sub-criteria and alternatives related to business intelligence tools and solutions. The spatial scope of this study is the National Iranian Oil Company as the largest producer of oil and petroleum products in Iran. The time scope of this study covers a period of 6 months from March 2012 to September 2012.

2.6 Limitations of Research

The main limitation of this study can be regarded as the complexity of obtaining the opinions of the experts. Another point is that theoretically, it is possible to consider even more criteria, sub-criteria or business intelligence tools in addition to what were included in the study. However, since the number of pairwise comparisons in AHP method for n factors is determined by $n(n-)/2$, and by increasing the number of factors or solutions, the number of pairwise comparisons will increase drastically, these leads to a significant increase in the number of the items of the questionnaire and the experts may refuse to answer them. Insufficient number of business intelligence experts in the organization and lack of their knowledge regarding the methods and concepts used in this paper made us to provide explanations regarding the questionnaires and to conduct interviews, resulting in more time spent on the collection of the data.

2.7 Implementation Stages of Research

This research was conducted in the following stages and Fig. 1 shows the executive model of the research:

Phase I: Identification of effective criteria and sub-criteria

- Identification of important criteria using desk study
- Collecting the experts' opinions using a Likert scale questionnaire and testing the hypotheses using Student's t-test method and determining and selecting the effective criteria, sub-criteria and alternatives

Phase II: Implementation of fuzzy AHP method for appraisal and ranking of business intelligence tools and solutions

- Prepare the hierarchical levels of criteria, sub-criteria and alternatives and coding them
- Create hierarchical tree model after identifying the criteria and sub-criteria and effective tools in the phase II
- Create a fuzzy AHP questionnaire for verbal scales
- Collect the experts' opinions in form of fuzzy numbers and preparing fuzzy pairwise comparison matrices and aggregating the experts' opinions (7 people)
- Calculate the consistency ratio of pairwise comparisons
- Calculate crisp matrix of aggregated experts' opinions using CFCS method (defuzzification)
- Calculate the final weights

Phase III: Implement of fuzzy TOPSIS method for evaluating and ranking business intelligence tools and solutions

- Prepare fuzzy TOPSIS questionnaire
- Obtain the opinions of the individuals regarding the importance of the criteria and the performance of each alternative against each criterion and preparing fuzzy decision matrix and matrix of relative importance of criteria for verbal scales
- Convert the judgments of experts into corresponding fuzzy numbers and aggregating their opinions using arithmetic mean
- Normalize fuzzy decision matrix and calculating the weighted normalized fuzzy decision matrix
- Determine positive and negative ideal points
- Calculate the distance of each alternative from positive and negative ideal points
- Calculate closeness coefficients and prioritizing the alternatives

Phase IV: Comparison of the two methods, i.e. fuzzy AHP and TOPSIS, and hypothesis testing using Spearman's rank correlation test

- Calculate the differences of the ranks and d^2 values.

3. Results

3.1 The Results Regarding the Effective Criteria and Sub-Criteria

In this section, based on the implementation stages of the research and given the research questions and research hypotheses for determining effective criteria and sub-criteria, the hypotheses of such criteria and sub-criteria were tested individually. The following example is only the first hypothesis and the same procedure applies to other criteria and sub-criteria. The initial data was collected using Likert scale, then it was studied, and analyzed using one-sample Student's t-test.

Hypothesis 1) "Technology" as a major criterion has a significant positive effect on the choice of business intelligence tools and solutions. The statistical hypotheses include:

$\begin{cases} H_0 : \mu < 3 & \text{Effect of "technology" on the choice of business intelligence tools and solutions is not high.} \\ H_1 : \mu \geq 3 & \text{Effect of "technology" on the choice of business intelligence tools and solutions is high.} \end{cases}$

| 1 | Determining the criteria and a sub-criteria of the problem by review of literature and evaluating the significance of their importance using Student's t-test method |

Fuzzy AHP

Step 1: Obtaining the hierarchical structure by finding the criteria, sub-criteria and alternatives

Step 2: Collecting experts' opinions in the form of fuzzy numbers and building fuzzy pairwise comparison matrices and aggregating the experts' opinions

Step 3: Calculating the consistency ratio (CR)

No

CR < 0.1?

Yes

Step 4: Calculating the crisp matrix of aggregated experts' opinions using CFCS method

Step 5: Calculating the final weights

Fuzzy TOPSIS

Step 1: Building fuzzy decision matrix and matrix of relative importance of criteria regarding verbal scales

Step 2: Normalizing fuzzy decision matrix and calculating the weighted normalized fuzzy decision matrix

Step 3: Determining the positive and negative ideal solutions

Step 4: Calculating the distance of each alternative from positive and negative ideal points

Step 5: Calculating the closeness coefficient and ranking the alternatives

Evaluating the correlation of ranks obtained by the two methods using Spearman's correlation coefficient technique

Fig. 1. Executive model of the research

The results of the statistical analysis of the questionnaires' data using one-sample t-test for the above hypothesis are given in Table 6. Given that after one-sample t-test analysis (assuming the error level of 0.05), a significant level less than 0.05 is achieved and the t-statistic value is positive, H_0 hypothesis is

rejected and H_1 hypothesis is confirmed. In other words, one can say, with confidence of 95%, that "Technology" index is important for the choice of business intelligence tools and solutions. In conclusion, one can say, with confidence of 95%, that "Technology" index influences the selection of business intelligence tools and solutions.

Table 6

One-sample t-test results for hypothesis

Index	Number	Mean	T-static	Sig*	Result
Technology	30	4.3333	4.817	0.000	Hypothesis confirmation (Rejection of H_0)

* $\alpha = 0.05$

Similarly, Table 7 shows the results of the tests of the hypotheses for all main criteria and sub-criteria. Accordingly, all of the selected criteria and sub-criteria were specified and included in Table 8, and the relevant studies mentioned here confirm their importance.

Table 7

The results of the hypotheses tests for all main criteria and sub-criteria

Criteria and sub-criteria	Average	Test	H_1: $\mu>3$	Sig.
Technology	4.33	4.817	Confirmed	0.00
Information integration	3.8	2.350	Confirmed	0.026
Metadata management	4.07	3.395	Confirmed	0.002
Monitoring of stored data	2.73	-0.724	Rejected	0.475
Data entry from other systems	2.33	-1.904	Rejected	0.067
Data warehouse	4.07	3.395	Confirmed	0.002
Intelligent agents	4.07	3.395	Confirmed	0.002
Multi-agent systems	1.67	-4.817	Rejected	0.000
Scalability	2.73	-0.724	Rejected	0.475
Developed tools	4.47	5.809	Confirmed	0.000
Advanced data analysis and delivery	4.73	9.355	Confirmed	0.000
Dashboard	4.6	7.180	Confirmed	0.000
Business analysis capability	2.47	-1.490	Rejected	0.147
Mobile BI	4.33	4.817	Confirmed	0.000
Dashboard power	2.47	-1.490	Rejected	0.147
Clustering problems	2.07	-2.841	Rejected	0.008
Financial analysis tools	1.8	-4.039	Rejected	0.000
Reporting tools OLAP	4.6	7.180	Confirmed	0.000
MCDM tools	1.8	-4.039	Rejected	0.000
Interactive illustration	4.07	3.395	Confirmed	0.002
Modeling of the status quo	2.2	-2.350	Rejected	0.026
Flexibility and ease of use	3.33	0.360	Rejected	0.722
Simulation models	1.67	-4.817	Rejected	0.000
Data mining techniques	3.53	1.490	Rejected	0.147
Text-mining	1.93	-3.395	Rejected	0.002
Export reporting to other systems	2.73	-0.724	Rejected	0.475
Reporting systems	3.8	2.350	Confirmed	0.026
Risk simulation	4.6	7.180	Confirmed	0.000
Company strength	4.6	7.180	Confirmed	0.000
Security	4.73	9.355	Confirmed	0.000
Retention	2.467	-1.490	Rejected	0.147
Response to market	2.73	-0.724	Rejected	0.475
Vendor experience	4.2	4.039	Confirmed	0.000
Sales strategy	2.6	-1.099	Rejected	0.281
Customer evaluation and prediction model	2.87	-0.36	Rejected	0.722
Financial stability of the vendor	1.67	-4.817	Rejected	0.000
Vendor relationships with strategic vendors	2.46	-1.49	Rejected	0.147
Vendor company size	2.33	-1.904	Rejected	0.067
Product quality	4.73	9.355	Confirmed	0.000
Innovation	1.53	-5.809	Rejected	0.000
Global reach and local presence	2.2	-2.350	Rejected	0.026
Ability to meet goals and commitments	2.6	-1.099	Rejected	0.281
Customization	2.87	-0.360	Rejected	0.722
After sales support	2.47	-1.490	Rejected	0.147
Network consulting	2.6	-1.099	Rejected	0.281
Required time for implementation	3.93	2.841	Confirmed	0.008
Warranty	1.93	-3.395	Rejected	0.002
Price of product	4.47	5.809	Confirmed	0.000
Vendors and educational partners	2.6	-1.099	Rejected	0.281
Learning techniques	2.067	-0.724	Rejected	0.475
Organizational access	2.067	-2.841	Rejected	0.008
Integration of organization	1.93	-3.395	Rejected	0.002
Simplicity	1.26	-9.355	Rejected	0.000
Adherence to the organizational governance	2.6	-1.099	Rejected	0.281
Organizational stability	2.73	-0.724	Rejected	0.475
Contract management	2.07	-2.841	Rejected	0.008
Permeability of each department	1.53	-5.809	Rejected	0.000

Table 8
Selected criteria and their references

Row	Criteria and sub-criteria	Studies
1 Technology		Power (2007), Vercellis (2009), Stair and Reynolds (2011), SAS Institute Inc. (2004),Williams and Williams(2007)
Metadata management		Qian-cheng (2007), Vercellis (2009), Moss and Atre (2003), Ranjan (2009).
Data warehouse		Tan et al. (2003), Vercellis (2009), Kimball et al. (1998), Dyche. (2000), Inmon (2002), Kimball and Ross (2002), Nemati et al. (2002),
Intelligent agents		Gao and Xu (2009), Lee et al. (2009), Rouhani, Ghazanfari and Jafari (2012)
Developed tools		Shi et al. (2007), Gao and Xu (2009)
Information integration		Herschel and Jones (2005), Bolloju, Khalifa and Turban (2002), Nemati et al. (2002) , Malone, Crowston and Herman (2003), hypatia research. (2009), Donald and Warner (2007), Sabanovic (2008),
2 Advanced data analysis and delivery		Power(2007),Vercellis(2009), Cooper et al. (2000), Thanassoulis(2001), Moss and Atre (2003), Naimuzzaman. (2009), Donald and Warner (2007)
Dashboards		Nemati et al. (2002), Hedgebeth (2007), Bose (2009), Warren et al. (2011), Stackowiak et al. (2007), Rouhani et al. (2012)
Reporting systems		Vercellis(2009), Stair and Reynolds (2011), hypatia research. (2009), Naimuzzaman (2009), Donald and Warner (2007)
Mobile BI		Bayer et al. (2011), Stipic and Bronzin (2011), Bensberg(2008), Zhu and Huang (2012), Stair and Reynolds (2011), Aydin and Halilov (2012)
OLAP		Tan et al. (2003), Lau et al. (2004), Rivest et al. (2005), Shi et al. (2007), Berzal et al. (2008), Lee et al. (2009), Ranjan (2009), Rouhani et al. (2012), Vercellis(2009),
Interactive illustration		Shmueli et al. (2010), Ranjan (2009), Sabanovic (2008), Rouhani et al. (2012)
Data mining techniques		Bolloju, Khalifa and Turban (2002), Shi et al. (2007), Berzal, Cubero and Jiménez (2008), Cheng, Lu and Sheu (2009), Tvrdikova (2007), Vercellis (2009), Hand,Mannila and Smyth(2001), Han and Kamber (2005),Hastie et al. (2001), Pyle (2003).
Risk simulation		Evers (2008), Galasso and Thierry (2008),Power(2007), Rouhani, Ghazanfari and Jafari (2012)
Flexibility and ease of use		Reich and Kapeliuk (2005), Zack (2007), Lin et al. (2009),Vercellis(2009), SAS Institute Inc. (2004), Işık(2010), Howson. (2008), Abzaltynova and williams(2009).
3 Company strength		SAS Institute Inc. (2004)
Security		Warren et al. (2011), Aydin and Halilov (2012), hypatia research. (2009), \ Imhoff. (2010), Yuen & Lau, (2008)
Vendor experience		Shmueli et al. (2010), Williams and Williams (2007), Donald and Warner (2007), Kumar et al. (2009), Amara, Y. et al. (2008)
Product quality		Vercellis(2009), Sanjay Kumar et al. (2009), Bross and Zhao (2004), Amara et al. (2008)
Support services		Shmueli, Patel and Bruce (2010), Macgllivray (2000)
Required time for implementation		Stair and Reynolds (2011), Kumar et al. (2009), Yuen & Lau (2008), Amara et al. (2008), Naimuzzaman(2009)
Price of product		Vercellis(2009), Stackowiak et al. (2007), Imhoff, (2010), Kumar et al. (2009), Adelakun and Kemper (2010), Amara et al. (2008)

3.2 Results of Fuzzy AHP Methodology Implementation

Step 1: Obtaining hierarchical structure by finding the criteria, sub-criteria and alternatives

As previously mentioned, the criteria and sub-criteria affecting ranking of the business intelligence tools include three main criteria, 19 sub-criteria are 6 alternatives and these have been obtained by review of the literature and obtaining the experts' opinions and after testing the hypotheses. After determining the criteria and sub-criteria, the conceptual model of the research and its hierarchical structure for ranking business intelligence tools and vendors has been constructed as it can be seen in Fig. 3. Table 9 shows the three-level hierarchy including objectives, criteria and sub-criteria and their codes.

Step 2: Collecting experts' opinions in form of fuzzy numbers and building fuzzy pairwise comparison matrices and aggregating the experts' opinions

Being provided with fuzzy AHP questionnaires, the experts were asked to express their opinions regarding the pairwise comparisons between the criteria in the first step, then concerning pairwise comparisons between the sub-criteria, and finally, comparisons between alternatives against sub-criteria in form of fuzzy scales. Consequently, the opinions of all the experts were gathered and fuzzy pairwise comparisons matrices were completed. Table 10 shows the aggregation of the experts' opinions (7 people) regarding pairwise comparisons between criteria obtained using arithmetic mean and by considering the objective of the problem and in from of triangle fuzzy numbers.

Table 9

The hierarchical levees of criteria, sub-criteria and alternatives with their code

Level I (Objective)	Criteria code	Level II (criteria)	Sub-criteria code	Level III (sub-criteria)	Level IV (alternatives)	Alternative codes
	C1	Technology	C11	Information integration		
			C12	Data warehouse		
			C13	Metadata management		
			C14	Intelligent agents		
			C15	Developed tools		
	C2	Advanced data analysis and delivery	C21	Dashboards		
			C22	Data Mining techniques	IBM	Alt 1
			C23	OLAP	Microsoft	Alt 2
			C24	Mobile BI	SAP	Alt 3
			C25	Risk simulation	QlikTech	Alt 4
			C26	Visual interaction	SAS	Alt 5
			C27	Flexibility and ease of use	Oracle	Alt 6
			C28	Reporting systems		
	C3	Company strength	C31	Security		
			C32	Vendor experience		
			C33	Product quality		
			C34	Price of product		
			C35	Required time for implementation		
			C36	Support services		
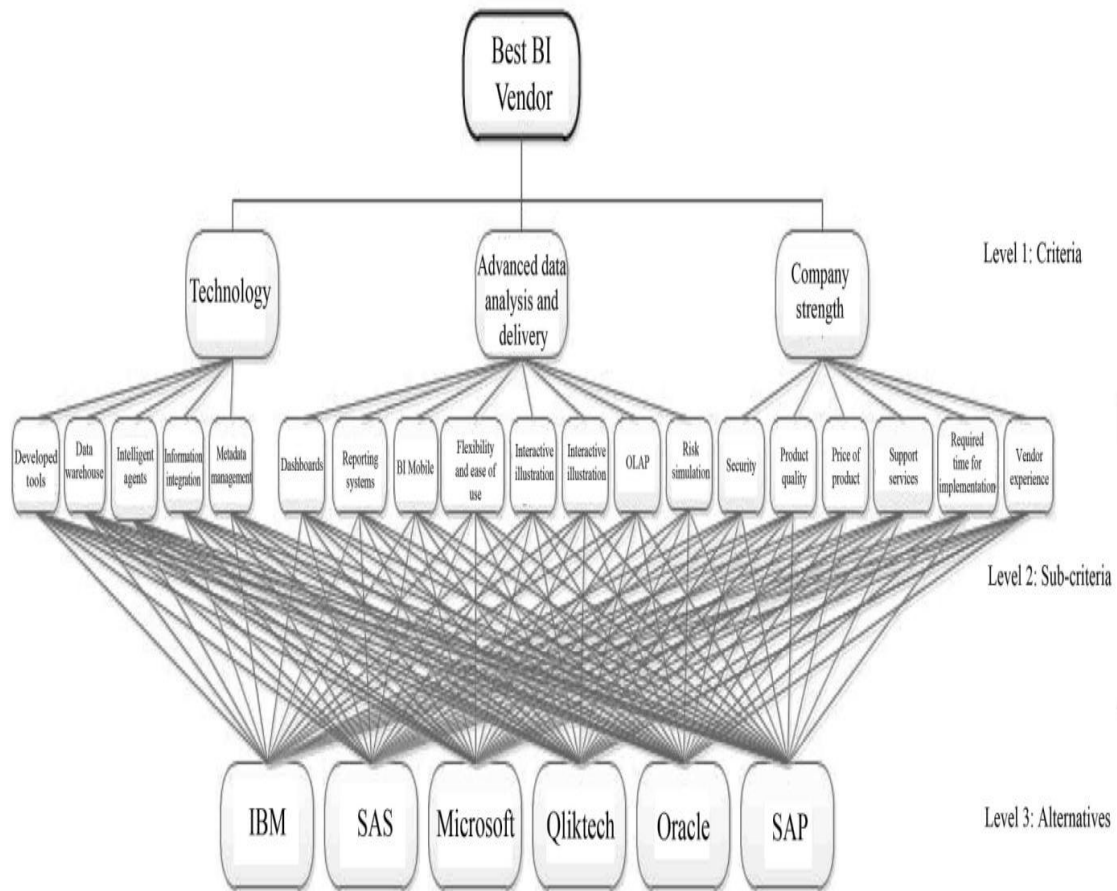
Fig. 3. The conceptual model of the research

Table 10
Aggregated experts' opinions for pairwise comparisons of level II (criteria)

Criteria	C1	C2	C3
C1	(1, 1, 1)	(1, 1.346, 1.601)	(1.739, 2.284, 2.779)
C2	(0.624, 0.743, 1)	(1, 1, 1)	(1.511, 2.119, 2.643)
C3	(0.36, 0.438, 0.575)	(0.378, 0.472, 0.662)	(1, 1, 1)

Step 3: Calculating the consistency ratio

To check the consistency of aggregated expert opinions regarding the first pairwise comparison matrix, which is shown in Table 10, a matrix of intermediate numbers was formed and the Eq. (6), Eq. (7) and Eq. (29) were used to calculate the largest eigenvalue λ_{max}.

$$\det(A - \lambda I) = 0 \Rightarrow \begin{bmatrix} 1-\lambda & 1.346 & 2.284 \\ 0.743 & 1-\lambda & 2.119 \\ 0.438 & 0.472 & 1-\lambda \end{bmatrix} = 0 \qquad (29)$$

Using equation 29, the largest eigenvalue of the matrix of intermediate numbers in Table 10 was 0.053; Hence:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} = \frac{(3.0055 - 3)}{(3-1)} = 0.0027 \qquad\qquad C.R. = \frac{0.0027}{0.58} = 0.0053 < 0.1$$

Thus, we conclude that the aggregated opinions for the first pairwise comparison matrix are consistent.

Step 4: Calculation of crisp matrix of aggregated experts' opinions using CFCS method

As mentioned earlier, after being ensured of the consistency of the opinions, matrix of pairwise comparisons must be converted from fuzzy scale to crisp scale, which is called defuzzification of fuzzy pairwise comparison matrix. In this research, equations 8 to 15 were used for defuzzification of fuzzy answers of the experts. Table 11 shows the results of defuzzification of the values in Table 10.

Table 11
The results of defuzzification of the values

Criteria	C1	C2	C3
C1	1	1.331604	2.237736
C2	0.772016	1	2.071574
C3	0.445693	0.486281	1

Step 5: Calculating the final weights

Finally and after calculating the non-fuzzy values of opinions, equation 16 is used to obtain the weights. Table 12 shows these weights.

Table 12
Crisp matrix of aggregated opinions and the final weight of the criteria

Criteria	C1	C2	C3	Weight
C1	1	1.331604	2.237736	0.4484
C2	0.772016	1	2.071574	0.3644
C3	0.445693	0.486281	1	0.1872

Fig. 4 illustrates the relative importance of the main criteria of the problem compared with each other

graphically. As this Figure and Table 10 show, the order of importance of criteria include technology, advanced data analysis and delivery and company strength. Results show that technology is the most important priority, then advanced data analysis and delivery in form of reports, followed by the strength of vendors and software companies.
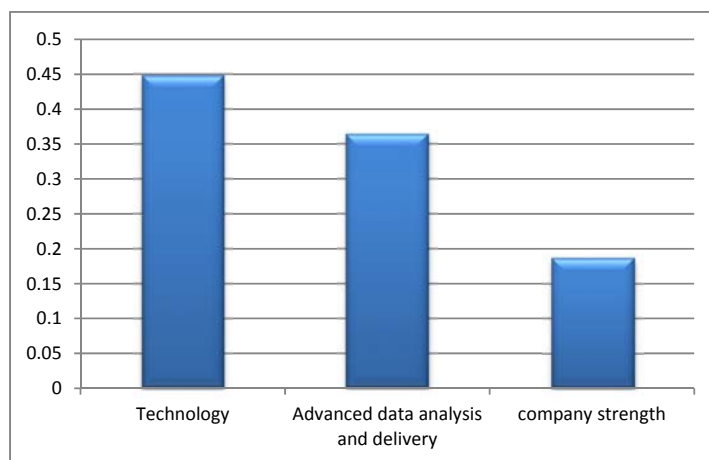
Fig. 4. Relative importance of criteria

Similarly, pairwise comparison matrices related to three sets of sub-criteria under each criterion were aggregated, reviewed for consistency, converted into non-fuzzy numbers and ultimately their final weights were calculated (Tables 13, 14 and 15).

Table 13
The crisp matrix of aggregated opinions and the ultimate weights of the sub-criteria related to technology criterion (CR= 0.065)

Sub-criteria	C11	C12	C13	C14	C15	Weight
C11	1	2.244235	3.039771	1.374425	2.264451	0.3399
C12	0.451642	1	2.824802	1.76802	1.73072	0.2423
C13	0.326099	0.351546	1	1.749658	1.407403	0.1433
C14	0.750222	0.582825	0.582664	1	1.092141	0.1428
C15	0.444418	0.590252	0.733906	0.963247	1	0.1317

Table 14
The crisp matrix of aggregated opinions and the ultimate weights of the sub-criteria related to advanced data analysis and delivery criterion (CR= 0.0743)

Sub-criteria	C21	C22	C23	C24	C25	C26	C27	C28	Weight
C21	1	0.571655	1.137106	3.789024	1.836886	1.552565	0.68986	0.690194	0.1328
C22	1.780132	1	0.999155	3.068386	3.05151	2.223608	1.015652	0.753311	0.1734
C23	0.89823	1.012053	1	5.435926	3.336901	4.239199	1.266887	1.611174	0.2123
C24	0.262498	0.328682	0.180317	1	0.63691	0.587145	0.562166	0.504602	0.0513
C25	0.553091	0.327953	0.30052	1.60229	1	1.520171	1.928036	1.764895	0.1034
C26	0.65155	0.458945	0.234944	1.736325	0.677518	1	0.480499	0.742465	0.0735
C27	1.475219	1.015652	0.802638	1.807685	0.526787	2.105711	1	1.506898	0.1342
C28	1.49878	1.361965	0.639068	2.007673	0.573144	1.385969	0.680728	1	0.1193

Table 15
The crisp matrix of aggregated opinions and the ultimate weights of the sub-criteria related to company strength criterion (CR= 0.0911)

Sub-criteria	C31	C32	C33	C34	C35	C36	Weight
C31	1	1.321258	0.807933	1.38186	1.611507	1.904419	0.2045
C32	0.770393	1	1.131916	1.915559	1.056762	1.960722	0.1956
C33	1.268738	0.897061	1	3.642385	3.436424	0.731684	0.2350
C34	0.733586	0.529496	0.269417	1	1.751069	1.579013	0.1293
C35	0.627758	0.9587	0.288345	0.595287	1	1.171978	0.1118
C36	0.541602	0.511301	1.406662	0.65597	0.87244	1	0.1238

To complete the remaining pairwise comparisons required for ranking the alternatives, 19 sub-criteria of the research and 6 alternatives should be compared in a pairwise manner. Table 16 summarizes all results of the weights of alternatives according to each sub-criterion.

Table 16
Alternatives weight matrix regarding the sub-criteria of the problem

Alternatives	C11	C12	C13	C14	C15	C21	C22	C23	C24	C25	C26	C27	C28	C31	C32	C33	C34	C35	C36
IBM	0.2052	0.2778	0.289360016	0.294553044	0.1913	0.1572	0.2919	0.4354	0.1716	0.2524	0.2216	0.0983	0.1279	0.1767	0.2418	0.3078	0.1592	0.1583	0.1113
Microsoft	0.1025	0.1019	0.101980727	0.075183013	0.0904	0.0803	0.0851	0.0812	0.0969	0.0924	0.0867	0.1255	0.0737	0.0827	0.0722	0.1089	0.337	0.2201	0.0978
SAP	0.2074	0.1317	0.135184305	0.137521416	0.105	0.1838	0.104	0.1354	0.1572	0.1367	0.1144	0.1485	0.1046	0.1447	0.0903	0.0932	0.1121	0.0702	0.1741
QlikTech	0.1225	0.0843	0.157577753	0.148196589	0.1896	0.2107	0.1597	0.1054	0.1996	0.1723	0.1913	0.3304	0.225	0.1892	0.1272	0.1213	0.1199	0.224	0.1622
SAS	0.1206	0.1509	0.124165084	0.180860982	0.2183	0.1738	0.2037	0.1389	0.2232	0.1945	0.2345	0.2045	0.2692	0.1552	0.2551	0.1795	0.1386	0.1833	0.1983
Oracle	0.2417	0.2534	0.191732114	0.16368495 6	0.2054	0.1941	0.1557	0.1037	0.1516	0.1517	0.1515	0.0929	0.1996	0.2514	0.2134	0.1894	0.1332	0.144	0.2563

For better understanding the results of the pairwise comparisons of the alternative against each sub-criterion, Fig. 5 illustrates the results of Table 16, and the performance of each alternative against each sub-criterion is shown in it.

However, for the final calculation of the weights of alternatives, in addition to the matrix of importance values given in Table 17, the final weight matrix of the sub-criteria is needed too. These are simply obtained by multiplying the weight of each criterion by the relevant sub-criteria. For example, in Table 17, we have $0.448 \times 0.3399 = 0.1524$. By matrix multiplication of Table 16, which is a 6×19 matrix, by

the final weight sub-criteria matrix as shown in Table 17, which is 1×19 matrix, the final 1×6 weight matrix of the alternatives are obtained. Fig. 6 shows the final weight of the alternatives.
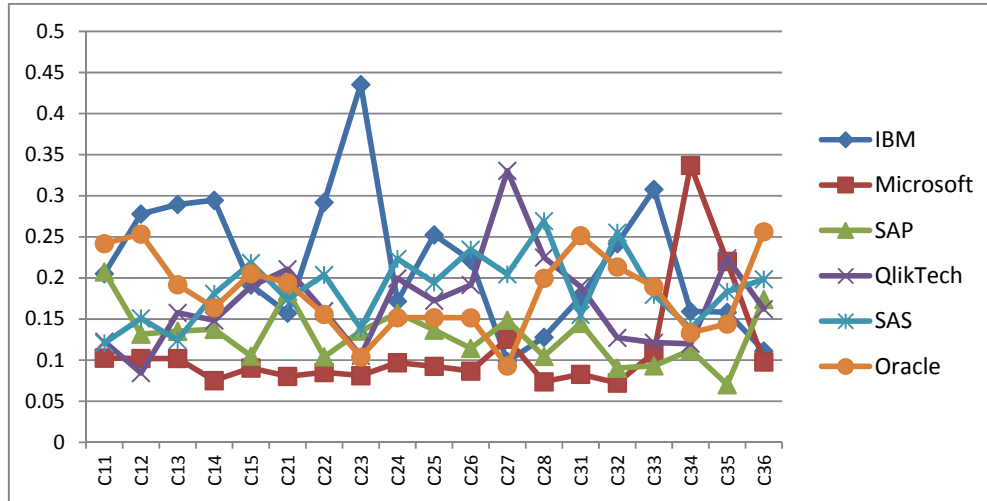

Fig. 5. Weigh performance of the alternatives against each sub-criterion

Table 17

Final weight of sub-criteria

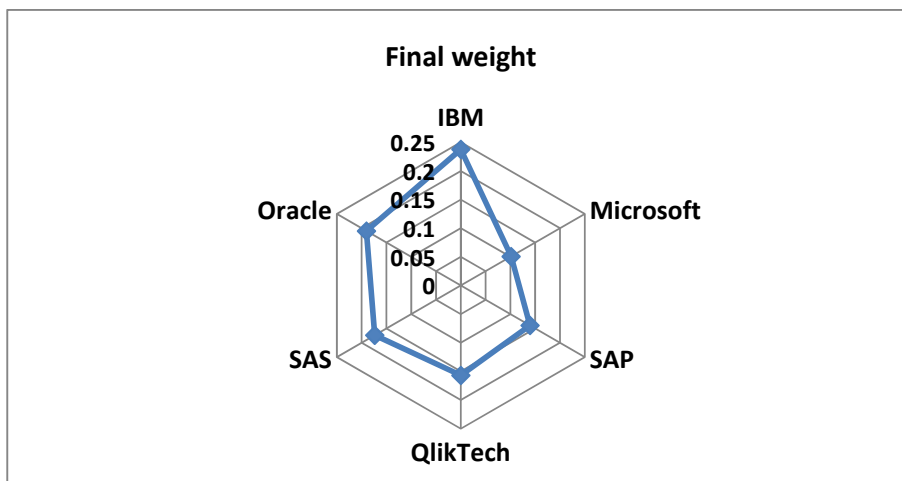| Criteria code	Criteria	Criteria weight	Sub-criteria code	Local weight of sub-criteria	Final weight of sub- criteria	Final weight of criteria
C1	Technology	0.448	C11	0.3399	0.1524	1
			C12	0.2423	0.1086	2
			C13	0.1433	0.0642	4
			C14	0.1428	0.0641	5
			C15	0.1317	0.0591	7
C2	Advanced data analysis and delivery	0.364	C21	0.1328	0.0484	9
			C22	0.1734	0.0632	6
			C23	0.2123	0.0773	3
			C24	0.0513	0.0187	19
			C25	0.1034	0.0377	13
			C26	0.0735	0.0268	15
			C27	0.1342	0.0489	8
			C28	0.1193	0.0435	11
C3	Company strength	0.187	C31	0.2045	0.0383	12
			C32	0.1956	0.0366	14
			C33	0.2350	0.0440	10
			C34	0.1293	0.0242	16
			C35	0.1118	0.0209	18
			C36	0.1238	0.0232	17

Fig. 6. Final weight of alternatives

The final weights and rank of each alternative as the final result of fuzzy AHP method are given in Table 18.

Table 18
Final weights and ranks of alternatives

Rank	Final weight	Alternatives
1	0.2378	IBM
2	0.1903	Oracle
3	0.1737	SAS
4	0.1569	QlikTech
5	0.1396	SAP
6	0.1016	Microsoft

The results of the ranking show that IBM is the first choice of the organization and this is due to its advantages in almost all criteria and sub-criteria. IBM is followed by Oracle, SAS, QlikTech, SAP and Microsoft, as it can be seen in Table 19.

Table 19
Comparing the companies based on their rankings

Company	Ranking in this study	World ranking
IBM	1	1
Oracle	2	7
SAS	3	2
QlikTech	4	9
SAP	5	8
Microsoft	6	5

In fact, among business intelligence super-vendors that includes IBM, Oracle, SAP and Microsoft, except for IBM and Oracle who have had ranked as the first and second, other super-vendors including SAP and Microsoft are ranked fifth and sixth. QlikTech and SAS that are classified as independent retailers in business intelligence market according to Gartner (Desisto, 2012), have been ranked as the fourth and fifth companies.

3.3 Results of Implementation of Fuzzy TOPSIS Methodology

As previously mentioned, for evaluation of criteria and sub-criteria and alternatives of business intelligence vendors, fuzzy TOPSIS method was used according to the following steps.

Step 1: Building fuzzy decision matrix and matrix of relative importance of criteria regarding verbal scales

Using the fuzzy TOPSIS questionnaire and the scale provided in Tables 20 and 21, the experts were asked to evaluate the order of importance of sub-criteria and performance of alternatives against each sub-criterion. Table 20 shows the experts' opinions regarding the importance of the sub-criteria. By converting each expert's judgments into fuzzy numbers and then averaging, the mean of the opinions will be determined. The mean of the experts' opinions on the importance of the sub-criteria are given in Table 20 and the mean of five sub-criteria of "technology" against alternatives are shown in Table 21.

Table 20
Opinions of seven experts regarding the importance of the sub-criteria

	Questionnaire 1	Questionnaire 2	Questionnaire 31	Questionnaire 4	Questionnaire 5	Questionnaire 6	Questionnaire 7
C11	H	MH	H	H	VH	VH	H
C12	MH	H	VH	MH	H	MH	VH
C13	MH	H	H	MH	VH	VH	VH
C14	H	H	H	H	MH	VH	H
C15	H	H	MH	M	VH	MH	VH
C21	VH	MH	H	H	VH	H	VH
C22	MH	VH	H	MH	H	VH	H
C23	VH	VH	H	M	MH	H	MH
C24	M	MH	H	M	MH	H	H
C25	M	MH	H	M	MH	M	MH
C26	ML	H	H	MH	MH	VH	VH
C27	H	H	H	ML	VH	H	VH
C28	H	H	H	MH	VH	MH	H
C31	VH	MH	VH	ML	MH	MH	VH
C32	MH	M	H	M	VH	VH	MH
C33	H	MH	VH	M	VH	VH	H
C34	MH	M	H	M	H	H	H
C35	MH	MH	H	MH	VH	H	VH
C36	H	MH	VH	H	VH	VH	H

Table 21
The mean of the experts' opinions on the importance of the sub-criteria

Alternatives	Mean of importance		
C11	0.729	0.9	0.986
C12	0.671	0.843	0.957
C13	0.729	0.886	0.971
C14	0.7	0.886	0.986
C15	0.643	0.814	0.929
C21	0.757	0.914	0.986
C22	0.7	0.871	0.971
C23	0.643	0.814	0.929
C24	0.529	0.729	0.886
C25	0.443	0.643	0.829
C26	0.614	0.786	0.9
C27	0.671	0.843	0.929
C28	0.671	0.857	0.971
C31	0.614	0.771	0.886
C32	0.586	0.757	0.886
C33	0.7	0.857	0.943
C34	0.557	0.757	0.9
C35	0.671	0.843	0.957
C36	0.757	0.914	0.986

Step 2: Normalizing fuzzy decision matrix and calculating the weighted normalized fuzzy decision matrix

It should be noted that in this study, all sub-criteria are considered positive, for example, a very good performance of an alternative in a sub-criterion such as "price of product" means its low price and its desirability on experts' opinion. This assumption helps us to obtain the opinions more easily and to normalize the decision matrix more conveniently.

After obtaining the normalized fuzzy decision matrix, the weights of the sub-criteria will be multiplied by the corresponding mean of performance of each alternative so that the weighted normalized fuzzy decision matrix can be constructed. Table 22 shows the result of this step just for two sub-criteria as examples. In Table 22, the normalized values are obtained by dividing all mean numbers of experts' opinions by the greatest upper limit of the mean expert opinions. Weighted normalized values are obtained by multiplying the weight of the first criterion by the corresponding normalized values.

Table 22
The mean of the experts' opinions on the performance of the alternatives against the sub-criteria

sub-criteria	alternatives	Mean of importance		
C11	Alt 1	8	9.5	10
	Alt 2	6	8	9.5
	Alt 3	6.667	8.5	9.667
	Alt 4	7.667	9.167	9.833
	Alt 5	6.667	8.5	9.667
	Alt 6	7	8.5	9.5
C12	Alt 1	7.333	9	9.833
	Alt 2	5.667	7.5	8.833
	Alt 3	7	8.667	9.667
	Alt 4	3	4.667	6.5
	Alt 5	6.333	8	9.167
	Alt 6	8.667	9.833	10
C13	Alt 1	7	8.833	9.833
	Alt 2	7	8.667	9.5
	Alt 3	7	8.833	9.833
	Alt 4	7.333	8.833	9.5
	Alt 5	7	9	10
	Alt 6	7.667	9.333	10
C14	Alt 1	7	8.833	9.833
	Alt 2	5.333	7.333	9
	Alt 3	7.333	9.167	10
	Alt 4	6	7.833	9
	Alt 5	6.667	8.5	9.667
	Alt 6	8.667	9.833	10
C15	Alt 1	7.333	9	9.833
	Alt 2	6.333	8.167	9.5
	Alt 3	6	8	9.5
	Alt 4	7	8.667	9.5
	Alt 5	8	9.5	10
	Alt 6	7.333	9	9.833

Step 3: Determining the positive and negative ideal solutions

Among the weighted normalized values, the greatest value and the lowest value are considered as the positive and negative ideal points for each batch of the data and for each of the sub-criteria. Regarding the data in Table 23, these points for the first sub-criteria are:

$$\text{positive ideal solution } A^+ = (0.582, 0.855, 0.985)$$

$$\text{negative ideal solution } A^- = (0.437, 0.72, 0.936)$$

Step 4: Calculating the distance of each alternative from the positive and negative ideal points

In this step, the distance of each of normalized weighted values from the positive and negative ideal points should be calculated according to Eq. 25. The sum of the distance values from the positive and negative ideal solutions will determine the ranking of the alternatives. Table 23 shows the distance value from positive and negative ideal points for the first sub-criteria. Obviously, the best alternative is the one that has the shortest distance from the positive ideal point and the longest distance from negative

ideal point in all sub-criteria.

Table 23
Weighted normalized values of performance of alternatives for sub-criteria 1 and 2

Sub-criteria	Weight			Alternatives	Mean of experts' opinions			Normalized values			Weighted normalized values		
1	0.7286	0.9	0.9857	1	8	9.5	10	0.8	0.95	1	0.583	0.855	0.986
	0.7286	0.9	0.9857	2	6	8	9.5	0.6	0.8	0.95	0.437	0.720	0.936
	0.7286	0.9	0.9857	3	6.667	8.5	9.667	0.6667	0.85	0.96667	0.486	0.765	0.953
	0.7286	0.9	0.9857	4	7.667	9.167	9.833	0.7667	0.91667	0.98333	0.559	0.825	0.969
	0.7286	0.9	0.9857	5	6.667	8.5	9.667	0.6667	0.85	0.96667	0.486	0.765	0.953
	0.7286	0.9	0.9857	6	7	8.5	9.5	0.7	0.85	0.95	0.510	0.765	0.936
2	0.6714	0.8429	0.9571	1	7.333	9	9.833	0.733	0.9	0.98333	0.492381	0.75857	0.94119
	0.6714	0.8429	0.9571	2	5.667	7.5	8.833	0.5667	0.75	0.88333	0.3804762	0.63214	0.84548
	0.6714	0.8429	0.9571	3	7	8.667	9.667	0.7	0.86667	0.96667	0.47	0.73048	0.92524
	0.6714	0.8429	0.9571	4	3	4.667	6.5	0.3	0.46667	0.65	0.2014286	0.39333	0.62215
	0.6714	0.8429	0.9571	5	6.333	8	9.167	0.633	0.8	0.91667	0.4252381	0.67429	0.8774
	0.6714	0.8429	0.9571	6	8.667	9.833	10	0.8667	0.98333	1	0.5819048	0.82881	0.9571

Step 5: Calculating the closeness coefficient and ranking the alternatives

All above steps and calculations are conducted for 19 sub-criteria and 6 alternatives, so that the distance of alternatives from positive and negative ideal points can be calculated and then closeness coefficient may be computed for each alternative. Table 24 summarizes the calculation results for alternatives. Fig. 7 illustrates closeness coefficient of alternatives graphically.

Table 24
The distance from positive and negative ideal solutions for the first sub-criteria

Sub-criteria	Weight			Alternatives	Mean of experts' opinions			Normalized values			Weighted normalized values			Distance from negative ideal	Distance from positive ideal
1	0.7286	0.9	0.9857	1	8.00	9.50	10.00	0.8	0.95	1	0.583	0.855	0.986	0.118	0.000
				2	6.00	8.00	9.50	0.6	0.8	0.95	0.437	0.720	0.936	0.000	0.118
				3	6.67	8.50	9.67	0.66667	0.85	0.96667	0.486	0.765	0.953	0.039	0.079
				4	7.67	9.17	9.83	0.76667	0.91667	0.98333	0.559	0.825	0.969	0.095	0.024
				5	6.67	8.50	9.67	0.66667	0.85	0.96667	0.486	0.765	0.953	0.039	0.079
				6	7.00	8.50	9.50	0.7	0.85	0.95	0.510	0.765	0.936	0.049	0.073
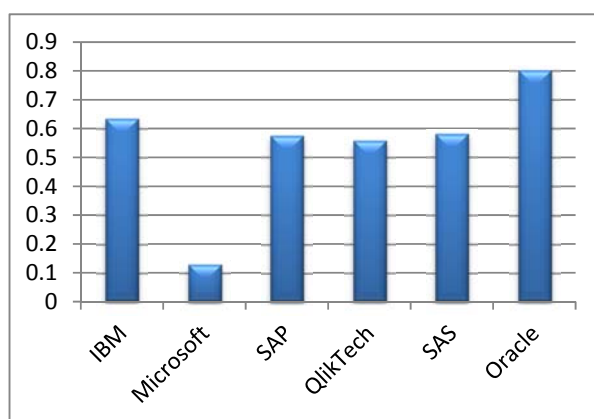
Fig. 7. Closeness coefficient of alternatives

Based on these results and unlike the results of fuzzy AHP method, here the first place is obtained by Oracle, followed by IBM, SAS and SAP. Interestingly, in both methods, Microsoft has the last ranking.

3.4 Comparison of two methods by evaluating correlation of rankings

For testing the second hypothesis, i.e. whether there is a significant relationship between the results of rankings of business intelligence tools using fuzzy AHP method and fuzzy TOPSIS method or not, Spearman's rank correlation test was used. Whenever the correlation between two set of variables is important and the data is collected as rankings (such as what we did with the final weights of fuzzy AHP method or closeness coefficients of fuzzy TOPSIS method), Spearman's rank correlation coefficient or Spearman's ρ can be used, which is one of the nonparametric methods (Behboodian, 1999). In this test, the null hypothesis is that there is no correlation, and the rank correlation coefficient is shown by r_s. Computation of rank correlation coefficient for pairwise data (x_i, y_i) for $i = 1, 2, \ldots, k$ is conducted as follows:

First of all x variables will be ranked based on their values, and we do the same for all y variables, then the difference between the scores of each pair will be calculated (represented by d_i). Then, square of the d_i will be calculated and finally, the rank correlation coefficient is calculated using the following equation (Azar, 2000).

$$r_s = 1 - \frac{6 \sum_{i=1}^{k} d_i^2}{n(n^2 - 1)} \tag{30}$$

Table 25 shows the results of the difference between ranking and d² values, while Table 26 represent the Spearman's correlation coefficient and the significance level using SPSS package for ranking the alternatives using FAHP and FTOPSIS methodology.

Table 25
Summary of the calculation of the weight and the final rankings of alternatives

Alternatives	d_i^-	d_i^+	CC_i	Final ranking
IBM	2.2634	1.2999	0.635192679	2
Microsoft	0.4572	3.0576	0.130084848	6
SAP	2.0420	1.5132	0.574364734	4
QlikTech	2.0017	1.5851	0.558078551	5
SAS	2.0573	1.4882	0.580256208	3
Oracle	2.8447	0.6999	0.802532715	1

Table 26
The results of the difference between rankings and d² values

Alternatives	Final ranking using fuzzy TOPSIS method	Final ranking using fuzzy AHP method	d	d²
IBM	2	1	1	1
Microsoft	6	6	0	0
SAP	4	5	-1	1
QlikTech	5	4	1	1
SAS	3	3	0	0
Oracle	1	2	-1	1

In short, we can say that after calculating the Spearman's correlation coefficient, a strong positive correlation at the significance level of 0.05 was observed between the business intelligence tools rankings using these two methods. The reasons for the differences in the results of the rankings will be discussed in detail in the next section.

4. Discussion and conclusion

The ranking of business intelligence vendors by Gartner (Desisto, 2012) is based on the parameters

specified by such companies in their annual statistical report, while the key indicators in this study were selected based on a comprehensive review of literature, and evaluation and ranking methods, namely fuzzy multi-criteria decision-making methods, and the measurement procedure is different from those offered by Gartner (Desisto, 2012). Other studies, such as Rouhani, Ghazanfari and Jafari (2012), Mojdeh (2007), Saadi (2012), Rezaie et al (2011) have studied organizational systems based on business intelligence indices, however in this research selecting and ranking of business intelligence vendors have been conducted for the first time, after identifying the integrated key indicators and criteria,.

Regarding the obtained results, it can be said that the results of investigating relative importance of the main criteria by conducting pairwise comparisons using FAHP and from the point of view of experts show that the order of importance of criteria include technology, advanced data analysis and delivery and company strength. The weights of these three criteria show that nearly 45 percent of the total relative importance is given to technology on the experts' opinions. As previously mentioned, by technology we mean the capacity of an organizations to collect, store, and organize knowledge. Common business intelligence technological activities include reporting, online analysis process reports, various types of analyses, data mining, process-mining, complex event processing, business performance management, benchmarking, predictive analysis and recommending analysis.

The fact that experts see technology as the most important criterion brings about another vital point for FAHP results, i.e. a vendor with better performance in its sub-criteria (information integration, data warehouse, metadata management, intelligent agents and developed tools) will ultimately obtain a higher rank. Vendor performance with respect to each criterion/sub-criterion in FAHP method shows that the most important sub-criterion for *technology* is *"information integration",* where Oracle, SAP and IBM respectively had better performance in comparison with other competitors on the experts' opinions. For the sub-criteria of the second criterion, namely "advanced data analysis and delivery", IBM has performed better than other competitors have and SAS and QlickTech have managed to win the second and third places. Another interesting point is the excellent performance of IBM for the most important sub-criteria of the second criterion, namely OLAP. For the sub-criteria of the third criterion, which ranks third in terms of the importance, Oracle has better overall performance than other competitors do. For the most important sub-criterion of the third criterion, namely "product quality", again IBM has earned the highest rank on the experts' opinions. For the first sub-criterion, the worst performance belongs to Microsoft. In fact, for all technology sub-criteria except for the second one, i.e. *"data warehouse"*, Microsoft has performed worse than all competitors. This is also more or less true for Microsoft regarding the second importance criteria, namely "advanced data analysis and delivery" and its sub-criteria except for "flexibility and ease of use". The performance of Microsoft is the worst one for seven sub-criteria of the second criterion. The poor performance of Microsoft on the experts' opinions is again obvious for the third criterion and its first, second and fifth sub-criteria, namely *security, vendor experience and support service*s and eventually Microsoft is ranked the last with a weight difference of 0.04 from SAP.

The results of fuzzy TOPSIS method show that Oracle is the first choice by the oil industry experts participating in this research. Appraisal of the importance of each of the 19 sub-criteria of the research using FTOPSIS method on the experts' opinions (that section of the questionnaire which deals with the sub-criteria) shows that the trend of importance for the sub-criteria of the first criterion is descending compared with the second sub-criteria, but it is somewhat ascending for the third criteria. The results of FTOPSIS method also can be explained as follows. Based on the distances from the positive and negative ideal points for each sub-criterion and for each alternative of the study, it can be seen that Microsoft has the worst performance for most sub-criteria (the largest proximity to negative ideal point and the longest distance from the positive ideal point), and Oracle has the best performance for majority of the sub-criteria (the longest distance from the negative ideal solution and the largest proximity to the positive ideal solution). Oracle has the best performance in information integration, developed tools,

OLAP, reporting systems, security and price product; while IBM has best performed for intelligent agents, dashboard, mobile BI, flexibility and ease of use, vendor experience, and product quality; the performance of QlikTech has been best for dashboard and risk simulation; SAP has the best visual interaction and support services, SAS has the most efficient data warehouse, required time for implementation, and Microsoft applications has the best performance in terms of developed tools.

This study has tried to provide an appropriate model for selection of business intelligence tools. In short, concerning the compare the results of these two methods, it can be said that after calculating Spearman's rank correlation coefficient, there was a strong positive correlation between the ranks of business intelligence tools obtained from FAHP and FTOPSIS methods ($\rho = 0.885$). However, it seems that the differences between the obtained results by the two methods can be explained by the following points:

1. Calculation mechanisms are largely different in two methods. In FAHP method, sum of the weights of each criterion and sub-criterion against pairwise comparisons determines the ranking of each alternative, however, in FTOPSIS method the ranks of the alternatives are determined based on their distance from positive and negative ideal solutions.
2. Scales of obtaining opinions do not coincide in these two methods, and it seems that the 9-point scale of pairwise comparisons in FAHP method provides greater scope for experts' opinion compared with 7-point scale used in FTOPSIS method for expressing the importance of the criteria and the performance of the alternatives.

Hence, it seems that FAHP method provides rankings that are more acceptable. In order to check the validity of the obtained results for oil industry, 7 senior managers were asked to express their opinions on the validity of the results. The results of this study showed that the results obtained by FAHP method are much more consistent with their opinions. They also stated that technology is the most effective criteria for selecting business intelligence tools. Another important criterion was advanced data analysis and delivery. Furthermore, using methods other than AHP, such as analytic network process (ANP) assuming the existence of relationships between indicators, or combination of fuzzy TOPSIS, ANP and fuzzy DEMATEL methods significantly reduces the number of pairwise comparisons among effective alternatives. Therefore, it can be suggested that these methods may be used for ranking business intelligence tools and comparing the results with the results of this research.

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