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A practical framework for assessing business intelligence competencies of enterprise systems using fuzzy ANP approach

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Abstract: As traditional concept in management, decision support had a remarkable role in competitiveness or survival of organisations and following, as modern impression, nowadays business intelligence (BI) has various applications in achieving desirable decision supports. Consequently, assessing BI competencies of enterprise systems can enable decision support in firms. This paper presents a practical framework for assessing the business intelligence capabilities of enterprise systems based on a set of novel factors and utilising fuzzy analytic network process (FANP). Through this, the construct of BI competency is decomposed into three main competency parts including 'managerial', 'technical' and 'system enabler' sub-goals, five main factors and 26 criteria. Using this framework, the BI competency level of enterprise systems can be determined which can help the decision makers to select the enterprise system that best suits organisations' intelligence decision support needs. In order to validate the proposed model, it is applied to a real Iranian international offshore engineering and construction company in the oil industry to select and acquire ERP system. This research provides a complete frame (factors, criteria and procedures) for firms to assess their proposed software and systems in the field of BI competencies and functions.

Keywords: business intelligence; BI; assessment model; fuzzy analytic network process; FANP; enterprise systems; enterprise resource planning; ERP.

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1 Introduction

We now live in an information society and more than ever managers are inundated with data. For managers to make the best possible decisions in the shortest amount of time, it is essential to turn data into structured information and then present this information to them in a format that is easy to read and that supports analysis. In recent years, software vendors have embraced this need and now numerous solutions, commonly referred to as business intelligence (BI), have emerged on the market, replacing the old concept of decision-support systems (DSSs) in organisations. In fact, nowadays, the individual-system approach applied to DSSs has been replaced by a new environmental approach. In the past, DSSs were independent systems in an organisation and had a tenuous relationship with other systems (silo systems). However, nowadays, enterprise systems (ESs) are the foundation of an organisation and practitioners design and implement BI as an umbrella concept, creating a decision-support environment for managers (Alter, 2004). The increasing trend to use intelligent tools in business systems has increased the need for BI competency assessment of ESs.

The BI competency assessment of ESs requires models and approaches that consider intelligence criteria besides the enterprises' usual functional and non-functional requirements and criteria. Reviewing the BI literature, one can infer that there have been some limited efforts to assess BI competences of ESs, which mainly viewed BI as an independent system isolated from the other ESs. In their work, Lönnqvist and Pirttimäki (2006) designed BI performance measures. After that, Elbashir et al. (2008) suggested measuring the effects of BI systems on the business process and provided some effective methods for the measurement. Lin et al. (2009) have also developed a performance assessment model for BI systems using ANP, which viewed BI as an independent system. The most related research work conducted in assessing the BI competences of ESs was

Ghazanfari et al. (2011) in which models for the BI assessment of ESs have been proposed. This model has been proposed based on the six factors namely ‘analytical and intelligent decision-support’, ‘providing related experimentation and integration with environmental information’, ‘optimisation and recommended model’, ‘reasoning’, ‘enhanced decision-making tools’ and finally, ‘stakeholder satisfaction’ using 34 criteria. The model can be applied to assess and rank ESs like enterprise resource planning (ERP), supply chain management (SCM) and customer relationship management (CRM) systems and so on based on their BI capabilities. Furthermore, Rouhani et al. (2012) proposed an evaluation model of BI for ESs using fuzzy TOPSIS. They utilised fuzzy TOPSIS approach to rank ESs, based their BI potentials. The purpose of the paper is to propose an approach to assess the BI competences of ESs in system selection phase of ESs life cycle. So, regarding Ghazanfari et al. (2011) model’ comprehensiveness in covering BI competency assessment criteria, the proposed model in the paper has been constructed based on this model.

The paper is arranged as follows. Section 2 provides a review on BI literature and definitions. Section 3, after explaining the method for analytic network processes (ANP) and the background of fuzzy sets, clarifies the fuzzy ANP algorithm which has been applied in this paper. The research method and proposed assessment model, based on the fuzzy ANP method is explained in Sections 4 and 5, respectively. In order to validate the proposed approach, a practical application of the proposed model is demonstrated in Section 6, through an assessment of three ERPs across the 26 criteria for a company in the oil industry. Conclusion appears in Section 7 and finally Section 8 explains research limitations and future researches.

2 Business intelligence

BI is a grand umbrella term introduced by Howard Dresner of the Gartner Group in 1989 to describe a set of concepts and methods to improve business decision-making by using fact-based, computerised decision support systems (Nylund, 1999). The first scientific definition, by Ghoshal and Kim (1086) referred to BI as a management philosophy and tool that helps organisations to manage and refine business information for the purpose of making effective decisions. The BI term can be used when referring to the following concepts (Lönnqvist and Pirttimäki, 2006):

1 related information and knowledge of the organisation, which describes the business environment, the organisation itself, the conditions of market, customers and competitors and economic issues

2 a systemic and systematic process by which organisations obtain, analyse and distribute the information for making decisions about business operations.

The concept of BI can be considered from three different perspectives namely ‘managerial’, ‘technical’ and ‘system enabler’. The managerial approach sees BI as a process in which data gathered from inside and outside the enterprise, are integrated in order to generate information relevant to the decision-making process. The technical approach considers BI as a set of tools that supports the process with the focus on technologies, algorithms and tools that enable the saving, recovery, manipulation and analysis of data and information. Finally, system enabler approach refers to BI systems as value-added features on supporting information (Ghazanfari et al., 2011). The purpose of BI is to help control the resources and the information flows of the business, which exist in and around the organisation. BI makes a large contribution to the required intelligence and knowledge of the organisations' management by identifying and processing data in order to explain their hidden meanings (Azoff and Charlesworth, 2004).

BI is the process through which organisations take advantage of information technology to collect, manage and analyse structural or non-structural data. In other words, the technology and commercial processing procedures in decision-making are supported through the extraction, integration and analysis of data. BI is an instrument of analysis providing automated decision-making about business conditions, sales, customer demand and product preference. It uses huge-database (data-warehouse) analysis, as well as mathematical, statistical, artificial intelligence, data mining and online analytical processing (OLAP). Eckerson (2010) argued that BI must be able to provide the production reporting tools, end-user query and reporting tools, OLAP, dashboard/screen tools, data mining tools and planning and modelling tools.

With considering BI as non-functional requirement of ES, we needs modes and frameworks to evaluate and ass this requirement in traditional ESs and software's and also in add-on tools and package which called business intelligence systems (BIS). To review the researches and studies in the field of BIS evolution, lack of literature is obvious. The related work in BIS evaluation started by, Lönnqvist and Pirttimäki (2006) designed BI performance measures. After that, Elbashir et al. (2008) suggested measuring the effects of BI systems on the business process and provided some effective methods for the measurement. Also Lin et al. (2009) have developed a performance assessment model for BI systems using ANP, which viewed BI as an independent system. The most related research work conducted in assessing the BI competences of ESs was Ghazanfari et al. (2011) in which models for the BI assessment of ESs have been proposed. Their model can be applied to assess and rank enterprise software based on their BI capabilities. Furthermore, Rouhani et al. (2012) proposed an evaluation model of BI for ESs using fuzzy TOPSIS. They utilised fuzzy TOPSIS approach to rank ESs, based their BI potentials. Recently Popovič et al. (2012) in near domain, has evaluated the effectiveness of BIS and proposed the model based on relationships between maturity, information quality, analytical decision-making culture and the use of information for decision-making as significant elements of the success of BIS. Following Işık et al. (2013) in BIS success domain have suggested a PLS model which emphasis that decision environment does influence the relationship between BI success and BI capabilities. This review prove the gap and lack for practical guidance include factors, criteria and process to assess ESs for their BI capabilities or evaluate BIS for their effectiveness.

3 Fuzzy analytic network process

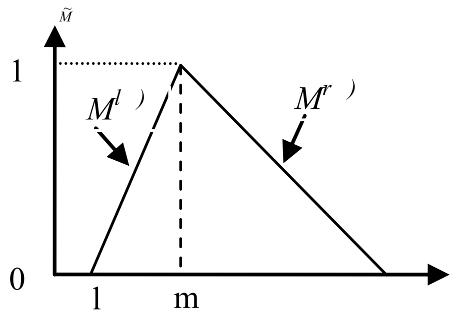
The fuzzy analytic network process (FANP) is applied to develop the BI competency assessment framework. Fuzzy set theory is also applied to deal with the uncertainties in the judgments made. This section has a brief review on the methods used in the paper.

3.1 Analytic network process

ANP as a generality of the analytic hierarchy process (AHP), was introduced by Saaty (1996). A decision-making problem in ANP technique is modelled through a net structure and the interactions between factors during the modelling process, feedbacks between factor clusters and inside dependencies in factor clusters are considered (Guneri et al., 2009). For example, in ANP the importance of the alternatives may have an effect on the importance of the criteria (Saaty, 1996). While AHP depicts a framework with a uni-directional hierarchical AHP relationship, the importance of the criteria determines the importance of the alternatives. Thus, a hierarchical structure with a linear, top-to-bottom form is not appropriate for a complex system. Saaty (1996) proposed the use of AHP to solve the problem of independence on alternatives or criteria and the use of ANP to solve the problem of dependence among alternatives or criteria.

The main difference between AHP and ANP is that ANP can handle interrelationships between the decision levels and criteria. ANP appears to be more accurate in complex situations due to its capability of modelling complex structures and the way that comparisons are performed. The method also provides an appropriate approach for defining relationships and interdependencies between criteria across and along the hierarchies (Boran and Goztepe, 2010).

Figure 1 A triangular fuzzy member



3.2 Fuzzy sets and numbers

In many real examples, the human preference model is uncertain and decision makers might be hesitant or unable to assign crisp values for judgments (Chan and Kumar, 2007; Shyur and Shih, 2006). Decision makers are often more interested in interval judgments than in making their judgments in crisp values (Amiri, 2010). The fuzzy set theory is introduced by Zadeh (1965, 1976) to cope with the vagueness and uncertainty related to information about several parameters. The use of a fuzzy set theory allows the decision makers to include qualitative information, incomplete information; non-obtainable information and somewhat unconfirmed facts into a decision model (Khalili-Damghani et al., 2012). A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characteriSed by a membership (characteristic) function, which assigns to each object a grade of membership ranging between zero and one. A tilde '~' is placed above a symbol if the symbol represents a fuzzy set. In applications, it is often convenient to work with triangular fuzzy numbers (TFNs) because of their simplicity (Aktan and

Samut, 2013) and they are useful in promoting representation and information processing in a fuzzy environment, Therefore in the current research TFN is chosen. A TFN is shown in Figure 1.

A TFN is denoted simply as (*l*/*m*, *m*/*u*) or (*l*, *m*, *u*). The parameters *l*, *m* and *u*, respectively, indicate the smallest possible value, the most promising value and the largest possible value that describe a fuzzy event. Each TFN has linear representations on its left and right side such that its membership function can be defined as (Ding and Liang, 2005):

$$\mu(x/\tilde{M}) = \begin{cases} 0, & x < l \\ (x-l)/(m-l), & l \le x \le m, \\ (u-x)/(u-m), & m \le x \le u, \\ 0 & x > u. \end{cases} \tag{1}$$

3.3 Fuzzy ANP algorithm

The fuzzy ANP method adapts the subjectivity of human judgment as being expressed in natural language. In reaching a conclusion, it is sometimes impractical and unclear whether to acquire exact judgments in pairwise comparisons. For instance, in a comparison between *X* and *Y* elements, it can be said that *X* is more strongly preferred than *Y*. However, if the question ''how strongly *X* dominates *Y*' is asked, the answer will not be exact. There is always an uncertainty in a decision-making process. The words used in the science of decision-making are always unclear and fuzzy. The fuzzy-based method, fuzzy ANP, is able to produce the required formation for uncertain and vague pairwise comparisons (Saaty, 1980).

In this study, the aim of Fuzzy ANP is to capture the fuzziness in the ESs comparison across BI capabilities criteria. Fuzzy ANP has some additional advantages comparing to the classical ANP method. It gives results that are more practical in a pairwise comparison process. Therefore, the method uses a linguistic scale, which helps the decision maker or the expert and provides a more flexible approach in reaching a conclusion. Fuzzy ANP method gives better clarification and learning in the decision-making process. Below, the main advantages of the fuzzy ANP against classical ANP are given (Chan and Kumar, 2007):

- it better models the ambiguity and imprecision associated with the pairwise comparison process
- it successfully derives priorities from both consistent and inconsistent judgments
- it is cognitively less demanding for the decision makers
- it is an adequate reflection of the decision-makers' attitude toward risk and their degree of confidence in the subjective assessments.

The fuzzy ANP method for assessment of BI competencies in ESs is constructed using Chang's extent analysis method (Chang, 1992, 1996), which has been widely used in the literature (Dagdeviren et al., 2008; Jajimoggala et al., 2011; Kahraman et al., 2006; Moalagh and Ravasan, 2013). Likewise, the method is relatively easier than other proposed approaches and is being used here. Variables for the extent analysis method are provided below:

Let $X = \{x_1, x_2,\ldots,x_n\}$ be an object set and $G = \{g_1,g_2,\ldots,g_m\}$ be a goal set. According to the model, each object is taken and an extent analysis is performed for each goal, g_i, respectively. Therefore, m (extent analysis values) for each object can be achieved with the following equations:

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

where all the $M_{gi}^{j}\,(j = 1, 2, \ldots, m)$ are TFNs. The steps of the method can be explained as below:

- *Step 1:* The value of fuzzy synthetic extent with respect to the i^{th} object is defined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} \tag{3}$$

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

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j}^{m} l_j, \sum_{j}^{m} m_j, \sum_{j}^{m} u_j \right) \tag{4}$$

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

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right] = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{5}$$

And then compute the inverse of the vector in equation (5) such that

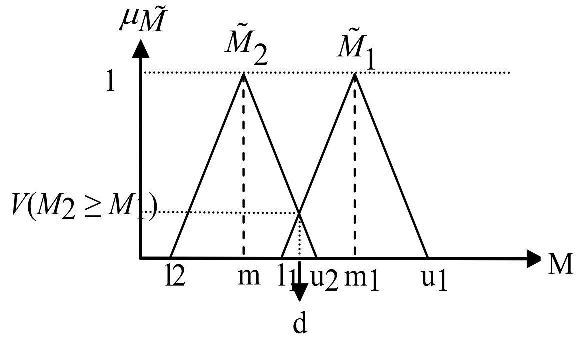
$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{6}$$

- *Step 2:* The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ 0, & \text{if } l_1 \geq u_2, \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - u_1)}, & \text{otherwise,} \end{cases} \tag{7}$$

where d is the ordinate of the highest intersection point D between μM_1 and μM_2 (see Figure 2) and $hgt(M_1 \cap M_2)$ is a separation index for two fuzzy numbers. The closer to 1 is $hgt(M_1 \cap M_2)$, the more difficult is to know whether M_2 is either greater or smaller than M_1. To compare M_1 and M_2, we both the values of $V(M_1 \geq M_2$ and $V(M_2 \geq M_1)$ are needed.

Figure 2 Intersection between M_1 and M_2



- *Step 3:* The degree 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

$$V(M \geq M_1, M_2, \ldots, M_k) = V(M \geq M_1) \text{ and } (M \geq M_2) \text{ and } \ldots \text{ and } (M \geq M_k) = \min V(M \geq M_i), \quad i = 1,2,\ldots,k. \tag{8}$$

Assume that

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

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

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

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

- *Step 4:* Via normalisation, the normalised weight vectors are:

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

Where W is a non-fuzzy number.

4 The assessment framework

For assessing the degree of BI competence level in each ESs, the model of Ghazanfari et al. (2011) as described in introduction, has been considered. The model is the only academic model articulated in the literature and regarding its comprehensiveness in covering BI competency assessment factors and criteria, has been deployed here. It seems that regarding the factors and criteria of this model (e.g., in stakeholders' satisfaction factor), it is best suited in BI competency assessment of implemented and live ESs. While the purpose of the paper is to provide a new approach to assess BI competency level in selection phase, the Ghazanfari et al. (2011) model should be customised for the research aim. So, the stakeholders' satisfaction factor eliminated from the available model and the new model proposed based on the rest five factors. Also, some criteria are merged into one. The clear concept and meaning conveyed in each of the five factors and 26 final criteria is described in below.

4.1 Analytical and intelligent decision-support (AIDS)

1 **Visual graphs:** it refers to ESs capability in preparing user friendly and graphical reports and even video or 3D graphics to users (Azadivar et al., 2009; Kwon et al., 2007; Li et al., 2008; Noori and Salimi, 2005; Power and Sharda, 2007).

2 **Alarms and warnings: i**t refers to ESs capability in providing alarms and warnings in pre-defined thresholds which is substantially common in large integrated ESs such as ERPs. This capability can help decision makers proactively respond to risky situations (Power, 2008; Ross et al., 2009; Xiaoshuan et al., 2009).

3 **OLAP:** OLAP tools enable users to interactively analyze multidimensional data from multiple perspectives which has been regarded as one of the most important capabilities of BI systems (Berzal et al., 2009; Lau et al., 2004; Lee et al., 2009; Rivest et al., 2005; Shi et al., 2007; Tan et al., 2003).

4 **Data mining techniques:** data mining, a brand new and interdisciplinary field of computer science is the process of discovering new patterns from large data sets involving methods at the intersection of artificial intelligence, machine learning, statistics and database systems which is considered as one of the most important capabilities of BI in ESs (Berzal et al., 2009; Bolloju et al., 2002; Cheng et al., 2009; Shi et al., 2007).

5 **Data warehouses:** data warehouse is a database of unique data structure that allows relatively quick and easy performance of complex queries over large amounts of data. Data warehouse is enables with extract, transform and load (ETL) capability which facilitates exchanging data from ES's databases to data warehouse. It has been noted that organisational databases without the proper capabilities of data warehouses would very unlikely lead to proceeds (Manh Nguyen et al., 2007; March and Hevner, 2007; Tan et al., 2003; Tseng and Chou, 2006).

6 **Web and e-mail channels:** World Wide Web (www) and internet has transformed the way people communicate and disseminate information. This media along with the emerging Web 2.0 and semantic web has been considered as one of the main types of media for publishing organisational reports on the web and should be taken into account in BI capabilities of ESs (Anderson et al., 2007; Oppong et al., 2005; Power, 2008; Tan et al., 2003). This criterion is also encompasses the capability of automatically sending required information and reports to pre-defined e-mail list (Wen et al., 2008).

7 **Mobile channel:** today, regarding the penetration of mobile devices in people everyday life, ESs should be empowered by mobile channel access to system functionalities and support managers by reports on their phones and handsets (Cheng et al., 2009; Power, 2008; Wen et al., 2008).

8 **Intelligent and multi-agents:** intelligent agent is an artificial agent operating in a software environment for doing pre-defined tasks which could be regarded as another BI capability of ESs (Gao and Xu, 2009; Lee et al., 2009; Ray et al., 2010; Yu et al., 2009). Also, some systems composed of multiple interacting intelligent agents known as multi-agent system for doing complicated tasks (Gao and Xu, 2009).

9 **Summarisation:** it refers to ESs capability in summarisation of information, while listing the main points in a brief and also in a comprehensive manner. This
capability is of more importance in reporting features of ESs (Bolloju et al., 2002; Hemsley-Brown, 2005; Power, 2008; Power and Sharda, 2007).

4.2 Providing related experiment and integration with environmental information (EXIN)

1 **Groupware:** groupware is a shared tool for disseminating and sharing data, information and knowledge which facilitates collaborative communication and group decision-making. Groupware is also provides required infrastructure for team and group working such as video conferences and documentation tools in a team working environment (Shim et al., 2002). Groupware has been regarded as one of the required factors in achieving BI competency in working systems (Damart et al., 2007; Marinoni et al., 2009; Reich and Kapeliuk, 2005).

2 **Flexible models:** it refers to ESs capability in defining and customising decision-making rules, generating tailor made reports, indicators and so on (Lin et al., 2009; Reich and Kapeliuk, 2005; Zack, 2007).

3 **Problem clustering:** it refers to ESs capability in automatic and intelligent clustering of issues and problems in an organisational context (Lamptey et al., 2008; Loebbecke and Huyskens, 2009; Reich and Kapeliuk, 2005).

4 **Import data:** data integration has been considered as one of the most important infrastructural requirements in the context of decision-making capabilities of ESs which refers to the ESs capability to extract and load required data to its database and convert it to an understandable format (Alter, 2004; Ozbayrak and Bell, 2003; Quinn, 2009; Shang et al., 2008).

5 **Export data:** it refers to ESs capability in exporting data and reports to other information systems, software packages and other facilities such as personal digital assistants (PDAs), mobile cell phones and so on (Ozbayrak and Bell, 2003; Shang et al., 2008; Shi et al., 2007).

6 **Combination of experiments:** tacit and explicit knowledge of human resource should be used to verify the information of ESs. The capability of acquisition and combination of managers' and employees' experiments is important characteristic for decision support. Historically, combination of experiments in knowledge management processes is classified as a significant requirement of decision-making in organisations (Courtney, 2001; Gonnet et al., 2007; Gottschalk, 2006; Hewett et al., 2009; Nemati et al., 2002; Ross et al., 2009).

7 **Environment and situation awareness:** it refers to ESs' capability in extracting environmental information such as technology trends, changes in rules and regularity, rivals, suppliers and customers related indicators (Koo et al., 2008; Phillips-Wren et al., 2004; Sen et al., 2009) and also situation specific information such as the time, place, person, challenges, possibilities and so on, to provide more accurate results (du Plessis and du Toit, 2006; Raggad, 1997).

4.3 Optimisation and recommended models (OPRM)

1 **Optimisation technique:** it refers to ESs capability in supporting complex arithmetic analysis either using regular techniques such as Simplex and goal programming or meta-heuristic methods and algorithms such as artificial neural network (ANNs), genetic algorithm (GA), ant colony (AC) and so on (Azadivar et al., 2009; Delorme et al., 2009; Lee and Park, 2005; Nie et al., 2009).

2 **Learning technique:** it refers to ESs learning capability in making decisions on the basis of prior decisions and the capability to learn from the historical data through discovering pattern and rules in decision-making process (Li et al., 2009; Power and Sharda, 2007; Ranjan, 2008).

3 **Simulation models:** in order to cut the costs and risks of doing real tests in operational environments, organisations need facilities that enhance simulation of the reality and analyse the potential impacts of the events and relevant risks. This capability can help decision makers either in decision-making process and outcomes (Power and Sharda, 2007; Quinn, 2009; Zhan et al., 2009).

4 **Evolutionary prototyping:** one important aspect of decision-making in every organisation, is knowledge about real specifications of a product or service. Evolutionary prototyping means capabilities of production or managerial systems to support information in design and production chains step by step. In industrial or facility systems, these capabilities are categorised in BI competencies of the system (Gao and Xu, 2009; Xiaoshuan et al., 2009).

5 **Dynamic prototyping:** in order to study the strength and weakness of execution processes, that is the result of decision-making, organisations need to prototype the process in a parametric environment. This capability supports decision-making process in terms of doing real time processes and is taken into account by researchers as a BI capability of ESs (Bolloju et al., 2002; González et al., 2009; Goul and Corral, 2007; Koutsoukis et al., 2000; Pitty et al., 2008).

6 **Dashboard/recommender:** every organisation, regarding its unique goals and business requirements needs some sorts of key performance indicators (KPIs) differ from others. This criterion indicates ES capability in providing effective and tailor-made dashboards for new cases in organisations' different hierarchical levels (Bose, 2009; Hedgebeth, 2007; Nemati et al., 2002).

4.4 Reasoning (REAS)

1 **Financial analyses tools:** financial function of every organisation was ever of a considerable attention in the past and today. Although analyses tools are of importance in organisations, but since financial analyses need special approaches and methods, the capability of an ES to provide these tools is regarded as an independent factor in BI competency assessment (Gao and Xu, 2009; Raggad, 1997).

2 **Backward and forward reasoning:** organisations' decision makers need ESs that justify the rational and reason of the decisions proposed by the system. Such a facility can help organisations in building trusty atmosphere with regard to the results suggested by the system (Evers, 2008; Gottschalk, 2006; Xiaoshuan et al., 2009).

3 **Knowledge reasoning:** knowledge is the result of high level ESs, formed by logical rules and support inferences in decision-making. The capability of inference by machine is one aspect of BI competencies of ESs. Providing reasons based on machine inference (expert systems) in organisational decision-making has been considered as an important and novel characteristic in BI by scholars and practitioners (du Plessis and du Toit, 2006; Evers, 2008; Ozbayrak and Bell, 2003).

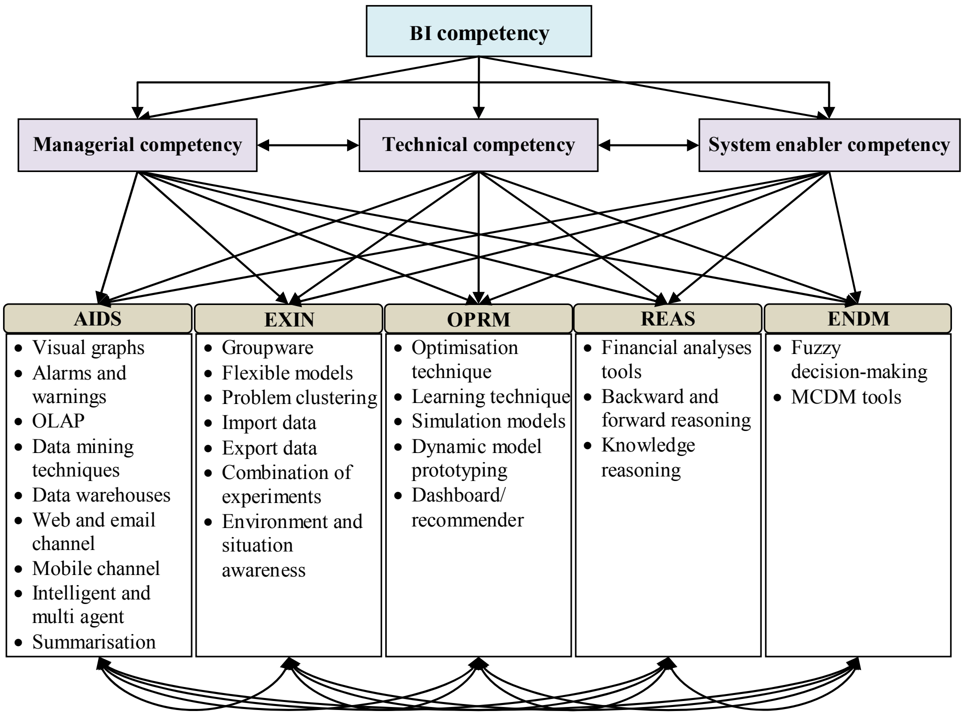
4.5 Enhanced decision-making tools (ENDM)

1 **Fuzzy decision-making:** the human preference model is uncertain and decision makers might be hesitant or unable to assign crisp values for judgments. Therefore, decision makers are often more interested in interval judgments rather than crisp values. Regarding this advantage, the capability of ESs in giving fuzzy values and manipulating fuzzy calculations has been observed as another BI competency (Makropoulos et al., 2008; Metaxiotis et al., 2003; Wadhwa et al., 2009; Yu et al., 2009; Zack, 2007).

2 **MCDM tools:** whether in our daily lives or in professional settings, there are typically multiple conflicting criteria that need to be assessed in making decisions. So, ESs should be enabled with multi-criteria decision-making (MCDM) tools to manipulate this situation (Hung et al., 2007; İç and Yurdakul, 2009; Marinoni et al., 2009; Yang, 2008).

As shown in Figure 3, the proposed model is composed of four hierarchical stages: goal, sub-goals, factors and criteria (listed in the box of factors), which are related to each other by means of conjunctive arrows. The BI competency assessment is the goal of the model and three perspectives of the concept of BI, 'managerial', 'technical' and 'system enabler' as discussed before are considered as the sub-goals of the model. The goal is connected to the sub-goals by three unidirectional arrows. The sub-goals also are connected to each other using bidirectional conjunctive arrows. The assessment factors are categorised into five main factors. The underlying factors belonging to each main factor are considered as the criteria. Each sub-goal related to the factors by single unidirectional arrows. Bidirectional arrows are also used to describe the inner dependencies among the factors and analyze their effects on each other.

Figure 3 The framework for BI competency assessment (see online version for colours)



The fuzzy ANP approach has been deployed for developing the model. The reasons for using an ANP-based approach for decision analysis in the paper are:

1 the BI competency assessment of ESs is a multi-facet problem

2 there are dependencies among factors and criteria in the assessment of BI

3 the detailed analysis of the inter-relationships among factors and criteria requires decision makers to reflect carefully on their priorities and on the decision-making problem itself.

Also, fuzzy ANP has some additional advantages over classical ANP method which makes it more appropriate for the paper. The reasons for using the fuzzy ANP approach for assessing BI competencies of ESs are:

1 vagueness and ambiguity in stating the status of ES in conceptual BI criteria

2 decision makers are on management level and prefer to assess by linguistic variables

3 fuzzy ANP can standardise the multi-criteria assessment problem with unique metrics.

In conclusion, these benefits made the fuzzy ANP an appropriate technique to be applied in the study.

5 Research methodology

The proposed model to assess BI competency level is composed of following steps:

Step 1 Establish a pairwise comparison team composed of IS experts.

Step 2 Determine the local weights of the sub-goals, factors and criteria by using pairwise comparison matrices. The fuzzy scale regarding relative importance (RI) to measure relative weights is displayed in Figure 4 and Table 1. This scale will be used in Chang's fuzzy ANP method.

Figure 4 Linguistic scale for relative importance

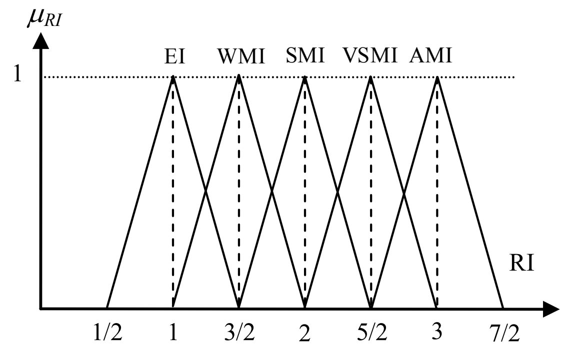


Table 1 Linguistic scales for relative importance

Linguistic scales	*Fuzzy number*	*Triangular fuzzy scale*	*Reciprocal fuzzy number*	*Triangular fuzzy reciprocal scale*
Equally important (EI)	$\tilde{1}$	(1/2,1,3/2)	$\tilde{1}^{-1}$	(2/3, 1, 2)
Weakly more important (WMI)	$\tilde{2}$	(1,3/2,2)	$\tilde{2}^{-1}$	(1/2, 2/3, 1)
Strongly more important (SMI)	$\tilde{3}$	(3/2,2,5/2)	$\tilde{3}^{-1}$	(2/5, 1/2, 2/3)
Very strongly more important (VSMI)	$\tilde{4}$	(2,5/2,3)	$\tilde{4}^{-1}$	(1/3, 2/5, 1/2)
Absolutely more important (AMI)	$\tilde{5}$	(5/2,3,7/2)	$\tilde{5}^{-1}$	(2/7, 1/3, 2/5)

Step 3 Determine the inner dependence matrix of each factor, with fuzzy scale (Table 1), with respect to other factors. This inner dependence matrix is multiplied with the local weights of the factors, determined in Step 2, to compute the interdependent weights of the factor.

Step 4 Calculate the global weights for the criteria. Global weights for the criteria are computed by multiplying local weight of the criteria with the interdependent weights of the factor to which it belongs.

Step 5 Measure the criteria using linguistic variables. The membership functions of these linguistic variables are shown on Figure 5 and the average values related with these variables are shown in Table 2.

Figure 5 Membership functions of linguistic values for criteria measuring

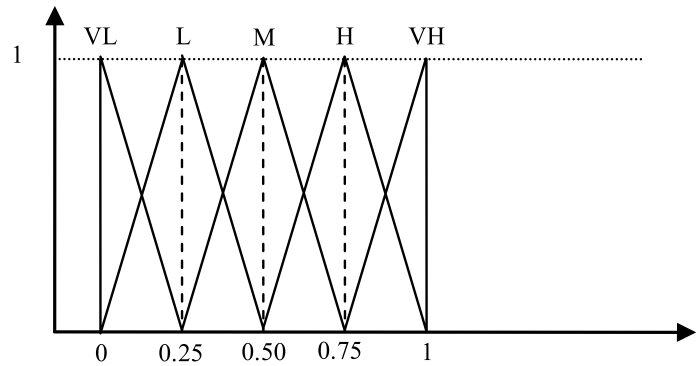
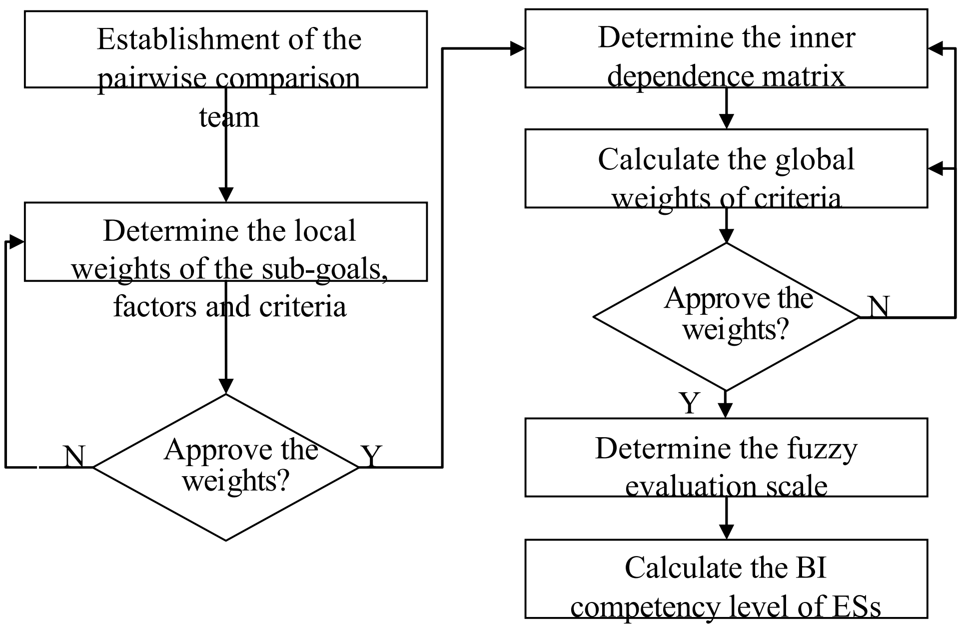


Table 2 Linguistic values and mean of fuzzy numbers

Linguistic values	*The mean of fuzzy numbers*
Very high (VH)	1.00
High (H)	0.75
Medium (M)	0.50
Low (L)	0.25
Very low (VL)	0.00

Figure 6 Schematic diagram of the research steps



Step 6 Calculate the BI competency level by using the global weights calculated in Step 4 for the criteria and the linguistic values determined in Step 5.

A Schematic diagram of the proposed steps is provided in Figure 6.

6 An illustrative example

This new approach to the assessment and selection of ESs was applied to the one of the great offshore engineering and construction companies in Iran’s oil industry to demonstrate its applicability and validity in practice. This company is an offshore general contractor to fabricate and install offshore facilities for the oil and gas industry. The five main business units of this company are finance and economics (FE), engineering and procurement (EP), logistics (LG), fabrication and operations (FO) and project management (PM). The management of this company, in consultation with information systems experts, decided to improve the decision support capabilities of their ESs as well as to replace existing and legacy systems with new, integrated ones. Meanwhile, the company objectives were to select and acquire an ERP system in order to facilitate integrated and real-time organisations’ transactions with the focus on decision support capabilities.

Based on a report that published in 2008, 42 vendors were active in Iran ERP market as a solution provider or implementer. 43% of these companies were agent of international and famous ERP providers and the others were the local companies. Although there is no clear report about the activity of international solution providers or their third party agents in Iran, but some large enterprises in automotive, mining, oil, gas, mill and consumer products have implemented and used such solutions. SAP, Oracle, IFS and Sage take the majority of international ERP market share in Iran (Amid et al., 2012; Nikookar et al., 2010).

For the purpose of system selection, the long and then short list of ERP vendors prepared by IS department experts. Finally, based on preliminary evaluations, three ERP vendors were announced to demo their system. Regarding the importance of BI capabilities of the system, the vendors were asked to present system capabilities with a focus on covering BI and decision support capabilities. The assessment were conducted by enterprise’s IS experts.

The proposed fuzzy ANP model, for this real application is explained as follow:

- *Step 1:* for the application, an expert team was formed from three IS experts of the company who has more than ten years of experience in the field and the authors of this paper. The proposed ANP model was explained to the experts and they were asked to do pairwise comparisons. Each expert was separately asked to describe the RI by means of linguistic variables in Table 1. In the cases where the assigned values were far from each other, they were asked to refine their judgment. Nevertheless, where consensus was not achieved, they were asked to explain why such values were assigned. Thus, one of the judgments was picked out on the basis of their explanations.

- *Step 2:* in this step, local weights of the sub-goals, factors and criteria which take part in the second, third and forth levels of hierarchical model, indicated in Figure 3 were calculated. Pairwise comparison matrices were formed by the expert team by using the scale given in Table 1. For example BI managerial and technical competencies were compared using the question ‘How important is managerial competencies when it is compared with technical competencies?’ and the answer
‘weakly more important’, to this linguistic scale was placed in the relevant cell against the TFNs $\tilde{2}$ or (1, 3/2, 2). All the fuzzy assessment matrices were produced in the same way. Pairwise comparison matrices were analysed by the Chang’s extent analysis method and local weights were determined. The local weights for the sub-goals were shown in Table 3.

Table 3 Local weights and pairwise comparison matrix of sub-goals

	Managerial	*Technical*	*System enabler*	*Weight*
Managerial	1#	$\tilde{2}$	$\tilde{3}^{-1}$	0.30
Technical	$\tilde{2}^{-1}$	1	$\tilde{2}^{-1}$	0.16
System enabler	$\tilde{3}$	$\tilde{2}$	1	0.54

After the determination of the sub-goals priorities, factors weights were defined on the basis of these sub-goals. Pairwise comparison matrices developed for this purpose are presented in Table 4 together with the calculated weights.

Table 4 Local weights and pairwise comparison matrix of factors

	AIDS	*EXIN*	*OPRM*	*REAS*	*ENDM*	*Weight*
Managerial						
AIDS	1	$\tilde{2}$	$\tilde{1}$	$\tilde{2}$	$\tilde{2}$	0.24
EXIN	$\tilde{2}^{-1}$	1	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	0.13
OPRM	$\tilde{1}^{-1}$	$\tilde{2}$	1	$\tilde{4}^{-1}$	$\tilde{1}$	0.19
REAS	$\tilde{2}^{-1}$	$\tilde{2}$	$\tilde{4}$	1	$\tilde{1}$	0.24
ENDM	$\tilde{2}^{-1}$	$\tilde{2}$	$\tilde{1}^{-}$	$\tilde{1}^{-1}$	1	0.20
Technical						
AIDS	1	$\tilde{2}^{-1}$	$\tilde{4}^{-1}$	$\tilde{2}^{-1}$	$\tilde{3}^{-1}$	0.00
EXIN	$\tilde{2}$	1	$\tilde{4}$	$\tilde{4}$	$\tilde{3}$	0.44
OPRM	$\tilde{4}$	$\tilde{4}^{-1}$	1	$\tilde{2}$	$\tilde{2}$	0.29
REAS	$\tilde{2}$	$\tilde{4}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{3}^{-1}$	0.04
ENDM	$\tilde{3}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{3}$	1	0.23

Table 4 Local weights and pairwise comparison matrix of factors (continued)

	AIDS	*EXIN*	*OPRM*	*REAS*	*ENDM*	*Weight*
System enabler						
AIDS	1	$\tilde{4}$	$\tilde{3}$	$\tilde{3}$	$\tilde{1}$	0.35
EXIN	$\tilde{4}^{-1}$	1	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	0.00
OPRM	$\tilde{3}^{-1}$	$\tilde{3}$	1	$\tilde{2}$	$\tilde{2}$	0.26
REAS	$\tilde{3}^{-1}$	$\tilde{3}$	$\tilde{2}^{-1}$	1	$\tilde{2}^{-1}$	0.16
ENDM	$\tilde{1}^{-1}$	$\tilde{2}$	$\tilde{2}^{-1}$	$\tilde{2}$	1	0.23

Global weights of factors were calculated as follow, by multiplying the weights listed in Table 4 with the sub-goals weights in Table 3:

$$W_{BI\ competency} = \begin{bmatrix} AIDS \\ EXIN \\ OPRM \\ REAS \\ ENDM \end{bmatrix} = \begin{bmatrix} 0.24 & 0.00 & 0.35 \\ 0.13 & 0.44 & 0.00 \\ 0.19 & 0.29 & 0.26 \\ 0.24 & 0.04 & 0.16 \\ 0.20 & 0.23 & 0.23 \end{bmatrix} \times \begin{bmatrix} 0.30 \\ 0.16 \\ 0.54 \end{bmatrix} = \begin{bmatrix} 0.26 \\ 0.11 \\ 0.24 \\ 0.16 \\ 0.22 \end{bmatrix}$$

In the last phase of this step, local weights of the criteria were determined by using the pairwise comparison matrices listed in Tables 5 to 9. The local weights calculated for criteria are given in the last column of the tables.

Table 5 Local weights and pairwise comparison matrix of AIDS criteria

Criteria	*Visual graphs*	*Alarms and warnings*	*OLAP*	*Data mining techniques*	*Data warehouses*	*Web and e-mail channels*	*Mobile channel*	*Intelligent and multi-agent*	*Summarisation*	*Weight*
Visual graphs	1	$\tilde{2}$	$\tilde{1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{4}$	$\tilde{4}$	$\tilde{4}$	$\tilde{1}$	0.14
Alarms and warnings	$\tilde{2}^{-1}$	1	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	$\tilde{2}$	$\tilde{2}^{-1}$	$\tilde{2}$	$\tilde{1}$	0.11
OLAP	$\tilde{1}^{-1}$	$\tilde{1}$	1	$\tilde{1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{2}^{-1}$	$\tilde{3}$	$\tilde{1}$	0.12
Data mining techniques	$\tilde{2}$	$\tilde{1}$	$\tilde{1}^{-1}$	1	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{3}$	$\tilde{4}$	0.15
Data warehouses	$\tilde{2}$	$\tilde{1}$	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	1	$\tilde{2}$	$\tilde{3}$	$\tilde{3}$	$\tilde{2}^{-1}$	0.13
Web and e-mail channels	$\tilde{4}^{-1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{1}$	$\tilde{2}$	$\tilde{2}$	0.09
Mobile channel	$\tilde{4}^{-1}$	$\tilde{2}$	$\tilde{2}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	$\tilde{1}^{-1}$	1	$\tilde{1}$	$\tilde{2}$	0.10
Intelligent and multi-agent	$\tilde{4}^{-1}$	$\tilde{2}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	1	$\tilde{2}^{-1}$	0.06
Summarisation	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	$\tilde{4}^{-1}$	$\tilde{2}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{2}$	1	0.10

Table 6 Local weights and pairwise comparison matrix of EXIN criteria

Criteria	*Groupware*	*Flexible models*	*Problem clustering*	*Import data*	*Export data*	*Combination of experiments*	*Environment and situation awareness*	*Weight*
Groupware	1	$\tilde{2}$	$\tilde{1}$	$\tilde{4}^{-1}$	$\tilde{4}^{-1}$	$\tilde{2}$	$\tilde{2}$	0.13
Flexible models	$\tilde{2}^{-1}$	1	$\tilde{2}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{1}$	0.12
Problem clustering	$\tilde{1}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{2}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}$	$\tilde{1}$	0.12
Import data	$\tilde{4}$	$\tilde{2}$	$\tilde{2}$	1	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	0.21
Export data	$\tilde{4}$	$\tilde{2}$	$\tilde{3}$	$\tilde{1}^{-1}$	1	$\tilde{2}$	$\tilde{3}$	0.22
Combination of experiments	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{2}$	0.11
Environment and Situation awareness	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	1	0.09

Table 7 Local weights and pairwise comparison matrix of OPRM criteria

Criteria	*Optimisation technique*	*Learning technique*	*Simulation models*	*Dynamic model prototyping*	*Dashboard/recommender*	*Weight*
Optimisation technique	1	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{2}$	0.35
Learning technique	$\tilde{2}^{-1}$	1	$\tilde{2}$	$\tilde{3}$	$\tilde{1}$	0.25
Simulation models	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{2}$	$\tilde{2}^{-1}$	0.13
Dynamic prototyping	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	1	$\tilde{2}^{-1}$	0.03
Dashboard/ recommender	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	$\tilde{2}$	$\tilde{2}$	1	0.23

Table 8 Local weights and pairwise comparison matrix of REAS criteria

Criteria	*Financial analyses tools*	*Backward and forward reasoning*	*Knowledge reasoning*	*Weight*
Financial analyses tools	1	$\tilde{2}$	$\tilde{2}^{-1}$	0.34
Backward and forward reasoning	$\tilde{2}^{-1}$	1	$\tilde{1}$	0.28
Knowledge reasoning	$\tilde{2}$	$\tilde{1}^{-1}$	1	0.38

Table 9 Local weights and pairwise comparison matrix of ENDM criteria

Criteria	*Optimisation technique*	*Learning technique*	*Weight*
Optimisation technique	1	$\tilde{1}$	0.50
Learning technique	$\tilde{1}^{-1}$	1	0.50

- *Step 3:* in this step, the degree of dependency among the factors was determined. Interdependent weights of the factors were calculated and the dependencies among the factors were considered. The degree of dependency among the factors was determined by analysing the impact of each factor on every other factor using pairwise comparisons. Based on these dependencies, pairwise comparison matrices were formed for the factors (Table 10).

Table 10 The inner dependence matrix of the factors

	EXIN	*OPRM*	*REAS*	*ENDM*	*Weights with respect to 'AIDS'*
EXIN	1	$\tilde{2}^{-1}$	$\tilde{3}^{-1}$	$\tilde{1}$	0.18
OPRM	$\tilde{2}$	1	$\tilde{2}$	$\tilde{2}^{-1}$	0.28
REAS	$\tilde{3}$	$\tilde{2}^{-1}$	1	$\tilde{1}^{-1}$	0.28
ENDM	$\tilde{1}^{-1}$	$\tilde{2}$	$\tilde{1}$	1	0.27
	AIDS	*OPRM*	*REAS*	*ENDM*	*Weights with respect to 'EXIN'*
AIDS	1	$\tilde{2}$	$\tilde{3}$	$\tilde{2}$	0.37
OPRM	$\tilde{2}^{-1}$	1	$\tilde{3}$	$\tilde{1}$	0.28
REAS	$\tilde{3}^{-1}$	$\tilde{3}^{-1}$	1	$\tilde{3}^{-1}$	0.05
ENDM	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	$\tilde{3}$	1	0.29
	AIDS	*EXIN*	*REAS*	*ENDM*	*Weights with respect to 'OPRM'*
AIDS	1	$\tilde{3}^{-1}$	$\tilde{1}$	$\tilde{1}$	0.14
EXIN	$\tilde{3}$	1	$\tilde{4}$	$\tilde{3}$	0.52
REAS	$\tilde{1}^{-1}$	$\tilde{4}^{-1}$	1	$\tilde{3}^{-1}$	0.08
ENDM	$\tilde{1}^{-1}$	$\tilde{3}^{-1}$	$\tilde{3}$	1	0.27
	AIDS	*EXIN*	*OPRM*	*ENDM*	*Weights with respect to 'REAS'*
AIDS	1	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	0.31
EXIN	$\tilde{1}^{-1}$	1	$\tilde{1}$	$\tilde{1}$	0.24
OPRM	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	1	$\tilde{3}^{-1}$	0.19
ENDM	$\tilde{3}^{-1}$	$\tilde{1}^{-1}$	$\tilde{3}$	1	0.26

Table 10 The inner dependence matrix of the factors (continued)

	AIDS	*EXIN*	*OPRM*	*REAS*	*Weights with respect to 'ENDM'*
AIDS	1	$\tilde{4}$	$\tilde{1}$	$\tilde{2}^{-1}$	0.30
EXIN	$\tilde{4}^{-1}$	1	$\tilde{3}^{-1}$	$\tilde{1}^{-1}$	0.15
OPRM	$\tilde{1}^{-1}$	$\tilde{3}$	1	$\tilde{2}$	0.32
REAS	$\tilde{2}$	$\tilde{1}$	$\tilde{2}^{-1}$	1	0.24

Using the computed relative importance weights, the dependence matrix of the factors was formed. Interdependent weights of the factors were computed by multiplying the inner dependence matrix of the factors (Table 10) with the local weights of factors

(Table 4). The interdependent weights of the factors were calculated as follow:

$$W_{BI\ competecny} = \begin{bmatrix} AIDS \\ EXIN \\ OPRM \\ REAS \\ ENDM \end{bmatrix} = \begin{bmatrix} 1 & 0.37 & 0.14 & 0.31 & 0.30 \\ 0.18 & 1 & 0.52 & 0.24 & 0.15 \\ 0.28 & 0.28 & 1 & 0.19 & 0.32 \\ 0.28 & 0.05 & 0.08 & 1 & 0.24 \\ 0.27 & 0.29 & 0.27 & 0.26 & 1 \end{bmatrix} \times \begin{bmatrix} 0.26 \\ 0.11 \\ 0.24 \\ 0.16 \\ 0.22 \end{bmatrix} = \begin{bmatrix} 0.23 \\ 0.18 \\ 0.22 \\ 0.16 \\ 0.22 \end{bmatrix}$$

Significant differences were observed in the results obtained for some factors weights when the interdependent weights of the factors were calculated. The differences are noticeable especially in EXIN (changes from 0.11 to 0.18).

- *Step 4:* using interdependent weights of the factors (Table 10) and local weights of criteria (Tables 5 to 9), global weights for the criteria were calculated in this step. Global criteria weights were computed by multiplying local weights of the criteria with the interdependent weights of the factors to which it belonged as shown in Table 11.

Table 11 Computed global weights of criteria

Factors	*Interdependent weights*	*Criteria*	*Weights (Tables 5 to 9)*	*Global weight*
AIDS	0.23	Visual graphs	0.14	0.033
		Alarms and warnings OLAP	0.11	0.025
		Data mining techniques Data warehouses	0.12	0.026
		Web and e-mail channels	0.15	0.033
		Mobile channel	0.13	0.030
		Intelligent and multi-agent	0.09	0.020
		Summarisation	0.10	0.023
			0.06	0.013
			0.10	0.024

Table 11 Computed global weights of criteria (continued)

Factors	*Interdependent weights*	*Criteria*	*Weights (Tables 5 to 9)*	*Global weight*
EXIN	0.18	Groupware	0.13	0.024
		Flexible models	0.12	0.021
		Problem clustering	0.12	0.021
		Import data	0.21	0.037
		Export data	0.22	0.039
		Combination of experiments	0.11	0.019
		Environment and situation awareness	0.09	0.016
OPRM	0.22	Optimisation technique	0.35	0.079
		Learning technique	0.25	0.055
		Simulation models	0.13	0.029
		Dynamic prototyping	0.03	0.007
		Dashboard/recommender	0.23	0.052
REAS	0.16	Financial analyses tools	0.34	0.053
		Backward and forward reasoning	0.28	0.044
		Knowledge reasoning	0.38	0.059
ENDM	0.22	Fuzzy decision-making	0.50	0.108
		MCDM tools	0.50	0.108

- *Steps 5–6:* in this stage, BI competency level of the three considered ERPs was determined by using the global weights of criteria (Table 11) and the opinions of three IS department experts on ERPs demo sessions by using linguistic measurement scale (Table 2). The calculations are shown in Table 12.

  Accordingly, BI competency level of the three considered ERPs was calculated as 0.395, 0.538 and 0.197 respectively. According to the final scores, the ERP2 has higher capabilities in fulfilling the enterprise's BI and decision support requirements. These achieved scores can be used besides the systems' scores for other functional and non-functional requirements in final system selection decision.

Table 12 Performance measured by using the proposed fuzzy ANP model

Factors	*Criteria*	*Global weight*	*Linguistic evaluations*			*Scale value*			*BI competency level*		
			ERP1	*ERP2*	*ERP3*	*ERP1*	*ERP2*	*ERP3*	*ERP1*	*ERP2*	*ERP3*
AIDS	Visual graphs	0.033	H	H	M	0.75	0.75	0.50	0.025	0.025	0.016
	Alarms and warnings	0.025	M	H	L	0.50	0.75	0.25	0.013	0.019	0.006
	OLAP	0.026	H	H	L	0.75	0.75	0.25	0.020	0.020	0.007
	Data mining techniques	0.033	M	M	VL	0.50	0.50	0.00	0.017	0.017	0.000
	Data warehouses	0.030	M	M	VL	0.50	0.50	0.00	0.015	0.015	0.000
	Web and email channels	0.020	H	H	M	0.75	0.75	0.50	0.015	0.015	0.010
	Mobile channel	0.023	H	H	M	0.75	0.75	0.50	0.017	0.017	0.011
	Intelligent and multi-agent	0.013	VL	M	VL	0.00	0.50	0.00	0.000	0.007	0.000
	Summarisation	0.024	H	H	M	0.75	0.75	0.50	0.018	0.018	0.012
EXIN	Groupware	0.024	M	M	VL	0.50	0.50	0.00	0.012	0.012	0.000
	Flexible models	0.021	VL	L	VL	0.00	0.25	0.00	0.000	0.005	0.000
	Problem clustering	0.021	VL	L	VL	0.00	0.25	0.00	0.000	0.005	0.000
	Import data	0.037	H	M	M	0.75	0.50	0.50	0.028	0.019	0.019
	Export data	0.039	M	H	H	0.50	0.75	0.75	0.019	0.029	0.029
	Combination of experiments	0.019	VL	M	VL	0.00	0.25	0.00	0.000	0.005	0.000
	Environment and situation awareness	0.016	VL	VL	VL	0.00	0.00	0.00	0.000	0.000	0.000

Table 12 Performance measured by using the proposed fuzzy ANP model (continued)

Factors	*Criteria*	*Global weight*	*Linguistic evaluations*			*Scale value*			*BI competency level*		
			ERP1	*ERP2*	*ERP3*	*ERP1*	*ERP2*	*ERP3*	*ERP1*	*ERP2*	*ERP3*
OPRM	Optimisation technique	0.079	L	M	VL	0.25	0.50	0.00	0.020	0.039	0.000
	Learning technique	0.055	L	H	VL	0.25	0.75	0.00	0.014	0.042	0.000
	Simulation models	0.029	M	M	L	0.50	0.50	0.25	0.015	0.015	0.007
	Dynamic prototyping	0.007	L	L	VL	0.25	0.25	0.00	0.002	0.002	0.000
	Dashboard/recommender	0.052	M	H	L	0.50	0.75	0.50	0.026	0.039	0.026
REAS	Financial analyses tools	0.053	H	M	L	0.75	0.50	0.50	0.040	0.027	0.027
	Backward and forward reasoning	0.044	VL	L	VL	0.00	0.25	0.00	0.000	0.011	0.000
	Knowledge reasoning	0.059	VL	M	VL	0.00	0.50	0.00	0.000	0.029	0.000
ENDM	Fuzzy decision-making	0.108	L	M	L	0.25	0.50	0.25	0.027	0.054	0.027
	MCDM tools	0.108	M	M	VL	0.50	0.50	0.00	0.054	0.054	0.000
Sum									**0.395**	**0.538**	**0.197**

7 Discussion and conclusions

This paper, first, elaborated on the importance of BI competency assessment. It was shown that assessing the level of BI competency of an ES is a difficult task with parameters that can be expressed in linguistic values. Such values are somewhat vague in essence and are subject to expert judgments which involve uncertainties. Therefore, the fuzzy ANP technique was employed to deal with this problem appropriately. Using ANP approach in weighting sub-goals, factors and criteria made it possible to consider a weighting model using RI of organisational requirements in ES's adaption comparing to previous models without any weighting method. Besides, the fuzzy approach is an applicable technique in providing decision makers with estimated values under uncertainty in the preference judgments. So, the fuzzy ANP approach has been applied in proposed BI competency assessment models.

Using this model, the state of BI capabilities of ESs can be determined. The framework breaks down BI capabilities level of ESs into three main sub-goals including 'managerial', 'technical' and 'system enabler'. These areas have been determined based on the BI definition approaches provided in the literature. The factors contributing to the BI competency assessment have been identified based on the Ghazanfari et al. (2011) model which have been customised and classified into five main factors of 'analytical and intelligent decision-support', 'providing related experiment and integration with environmental information', 'optimisation and recommended model', 'reasoning' and 'enhanced decision-making tools', with 26 related criteria. The proposed model was then applied to an offshore engineering and construction company in Iran's oil industry to measure the BI competencies of ERP system in system selection phase. Finally, by computing the final competency level for each ERP system and comparing them, the ranking of the assessed ERPs was presented. Survey which has done after a time period after ERP implementation shows the satisfaction of stakeholders in BI capabilities of selected ERP and confirms the effectiveness of the proposed framework.

To compare the results of current research with related works, the nearest works are the first Rouhani et al. (2012) which they proposed an evaluation model of BI for ESs using fuzzy TOPSIS, but in this research, the developed framework is holistic and has the two parts of weighing and ranking. The second near work is Lin et al. (2009) which they developed a performance assessment model for BI systems using ANP and they viewed BI as an independent tool however in this research we have utilised FANP practically with approach of ESs and their BI competencies.

The major contributions of this research are as follows. First, this paper, demonstrated the significance of BI competency assessment in ESs. Second, a fuzzy ANP framework for BI competency assessment has been proposed with the goal of extending the current literature in the field. The framework facilitates assessing the BI capabilities of ESs and a corresponding fuzzy ANP architecture that supports and coordinates the work of decision-making in real problems. Third, this paper presents an application of the proposed framework to a real case. To sum up, this model provides an assessment of the BI requirement of an ESs which encompasses the nonlinear relationships among interdependent levels. The authors believe that the proposed model and results of the paper can help practitioners assess, select and acquire ESs more appropriately, regarding their BI and decision support requirements. Additionally, using this model, the current state of BI capabilities or competences of an ESs and possible areas of improvements can be identified in order to improve the decision-making environment of an organisation.

8 Limitations and future researches

Although, the proposed model is a practical tool for real case problems, but using the model in other cases depends heavily on the priorities and unique requirements of the organisation under study and thus is case dependant. The weights of criteria and competency of ESs fit for one case are not necessarily applicable for another one. Thus, all the expert judgments in pairwise comparisons must be changed for any new case. Therefore, caution should be exercised in generalising the proposed model to further organisations. However, since the achieved results were heavily dependent on experts' competence and proficiency both in the subject of BI and business requirements, it functioned as the main limitation of the present study. Another limitation of the study is that the model presented here does not consider all the possible factors and criteria might be associated with BI competency assessment. However, this model can be applied across numerous ESs.

Although the case study demonstrated the usefulness of the model for BI competency assessment, we believe that there is still room for future validation and improvement. Further research is necessary to fine tune the proposed model and to compare the efficiency of different models for measuring BI competency level. Applying other MCDM methods in a fuzzy environment to assess ESs by considering BI criteria and comparing the results of these methods is also recommended for future research. Furthermore, since the proposed method involves a large amount of numerical computations, a user-friendly intelligent Decision Support System (DSS) have to be developed to save time and efforts in both making pairwise comparisons and interpreting the results of the fuzzy ANP. Besides, developing a group decision-making system can be very useful. In this way, the opinions of different authorities can be taken into account. Also, different hierarchical and detailed objectives can be incorporated into the study. Additionally, mathematical models or meta-heuristics can be combined with the existing method.

As the proposed model draws up on the Ghazanfari et al. (2011) model, future research works may follow to extend the main factors of this model by adding new factors. Furthermore, proposing a new comprehensive method to large ESs' selection especially ERPs, using conventional functional and non-functional requirements besides BI requirements, is highly recommended for future research.

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