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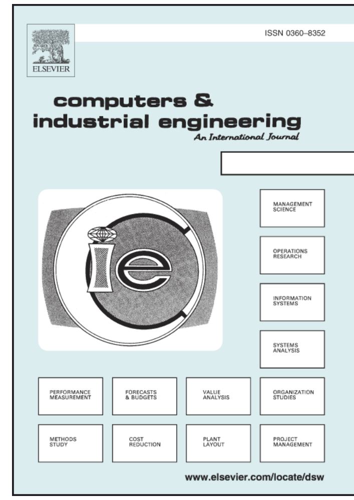

Using quality function deployment to conduct vendor assessment and supplier recommendation for business-intelligence systems

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Abstract

Business intelligence (BI) has been recognized as an important enterprise information system to help decision makers achieve performance measurement and management. Generally, typical BI users consist of financial analysts, marketing planners, and general managers. However, most of them are not familiar with BI's core technologies. In order to help corporate executives better assess BI vendors, evaluation criteria are separated into marketing requirements (MRs) and technical attributes (TAs), respectively. In particular, a fuzzy MCDM (multi-criteria decision making) based QFD (quality function deployment) is proposed as follows: (1) fuzzy Delphi is used to aggregate the performance scores of BI vendors, (2) fuzzy DEMATEL (decision making and trial laboratory) is conducted to recognize the causalities between MRs and TAs, and (3) fuzzy AHP (analytical hierarchy process) is employed to recommend optimal BI systems. For better benchmarking, the strengths and weaknesses of three competitive BI vendors (i.e. SAP, SAS, and Microsoft) are concurrently visualized through displaying a line diagram (in terms of TAs) and a radar diagram (in terms of MRs). More importantly, experimental results demonstrate that supplier assessment and supplier recommendation have been successfully accomplished.

Keywords: business intelligence, vendor assessment, supplier recommendation, QFD.

1. Introduction

In recent years, rapid advances in information technologies, such as data warehousing and data mining, coupled with urging requirements on performance management and corporate diagnosis embarks the popularity of business intelligence (Chen et al., 2012). Different from the wave of "operational" enterprise resource planning (ERP), "strategic" business intelligence (BI) started to emerge as an umbrella in mid 1990s to cover software-enabled business planning, business analytics and integration with the area of big data. Specifically, the need to adopt ERP results from business process reengineering (BPR) while the main reason to implement BI originates from the concept of decision support systems (DSS). Referring to Eckerson (2003), the main benefits of adopting BI for an organization are summarized in Fig. 1 for reference.

According to Gartner's report (Ravi, 2012), Fig. 2 demonstrates the top five key players in the BI market, including SAP (21.6%), Oracle (15.6%), SAS (12.6%), IBM (12.1%) and Microsoft (10.7%). Obviously, different players have their relative strengths and weaknesses on handling large volumes or high-dimensional big data, dealing with data velocity, data variety (structured and unstructured), and data visualization (dashboards and scorecards). As we know, SAP and Oracle already owns a huge market base in the ERP (enterprise resource planning) field. In addition, SAS is a well-known statistics package provider and Microsoft is the dominant player in the operating systems of personal computers. Today, owing to huge investment on enterprise resource planning (ERP), supply chain management (SCM), customer relationship management (CRM), and product lifecycle management (PLM), enterprise software selection has become much more important than before (Turban et al., 2007). In particular, choosing software platform is quite different from buying products or services in many ways because software needs to be “maintained”, “updated”, and “repaired” (Büyüközkan and Feyzioğlu, 2005; Motwani et al., 2005).

In choosing an enterprise software package and planning for the overall project, managers or executives need to answer the following questions (Ngai et al. 2008; Tsai et al., 2012a; 2012b): (1) Why do you want to implement BI? (2) What are your business requirements? (3) What is your expected ROI (return on investment)? However, during the process of software implementation and customization, they are often frustrated in integrating legacy systems, identifying key performance indicators, and constructing a causal system to perform corporate diagnoses. Therefore, Turban et al. (2008) suggested considering the following questions prior to implementing the BI systems: (1) reporting what happened in the past, (2) analyzing why it happened, (3) monitoring what is happening now, (4) indicating which actions should be taken and (5) predicting what will happen in the future.

Needless to say, technical features are more easily measured than non-technical (marketing) features when assessing software/platform vendors. For convenience, a brief comparison between various information technologies is described in Table 1. In reality, typical BI users involve financial analysts, marketing planners, and general managers (Elbashir et al., 2013). Usually, most of them may not have sufficient MIS/IT backgrounds. Based on the theory of TAM (technology acceptance model), software users do not care about whom they buy from, but they concern more about perceived usefulness and ease-of-use (Amoako-Gyampah, 2007; Chang et al., 2014). In order to highlight the importance of non-functional features, a QFD (quality function deployment) based framework is implemented in this context to consider two distinct aspects: marketing requirements (MRs) and technical attributes (TAs).

More importantly, this paper presents an integrated framework to help business planners conduct vendor assessment, supplier selection and product (software) recommendation. In particular, several critical issues are addressed as follows:

- *By taking the interdependences between MRs and TAs into account, the importance weights of MRs and TAs are derived accordingly,*

- *To carry out supplier selection, the relative strengths and weaknesses of the competitive BI vendors are visualized and displayed in terms of MRs and TAs,*
- *User preferences for MRs are incorporated to conduct supplier recommendation in an unsupervised manner for accommodating the inexperienced BI users.*

The remainder of this paper is organized as follows. Section 2 introduces vendor evaluation based on quality function deployment. Section 3 introduces the proposed framework composed of fuzzy DEMATEL, fuzzy Delphi, and fuzzy AHP. A real example to benchmark three representative BI vendors is illustrated in Section 4. Conclusions and future works are drawn in Section 5.

[Fig. 1. – Fig. 2. Here]

[Table 1 Here]

2. QFD based supplier assessment and software recommendation

By means of the quality function deployment (QFD), this study attempts to conduct supplier evaluation and recommendation in terms of two aspects, including marketing requirements and technical attributes. Quality function deployment (Akao, 1970) originated in Japan has been widely applied to numerous areas for product development, concept evaluation, service design, and competitor benchmarking. Generally, the QFD is characterized by a set of marketing requirements (MRs) associated with technical attributes (TAs). Typically, the conventional QFD consists of the following four phases (Büyüközkan and Feyzioğlu, 2005; Wang and Chen, 2012): phase one translates marketing requirements into technical attributes; phase two translates technical attributes into part characteristics; phase three translates part characteristics into manufacturing operation, and phase four translates manufacturing operations into production requirements.

As shown in Fig. 3, the conventional QFD prioritizes the weights of MRs and TAs, independently, without considering the interdependences or the correlations among themselves. For evaluating the benchmarking competitors, marketing assessment (in terms of MRs) and technical assessment (in terms of TAs) should be considered in an interdependent manner. In order to relate TAs to MRs, the whole process is conducted below (suppose there are "*m* MRs" and "*n* TAs"):

$$R_{ji}' = \frac{\sum_{k=1}^{n} R_{ki} \times \gamma_{kj}}{\sum_{j=1}^{n}\sum_{k=1}^{n} R_{ki} \times \gamma_{kj}}, \tag{1}$$

$$Ps_{CRi} = \sum_{j=1}^{n} Ps_{TAj} \times R_{ji}', \quad 1 \le i \le m \tag{2}$$

where Ps_{CRi} and Ps_{TAj} are the performance scores of MR_i and TA_j, R_{ki} (R_{ji}') stands for the (normalized) dependences between MR_i and TA_j, and γ_{kj} denotes the correlations among the TAs.

[Fig. 3. Here]

2.1 Vendor assessment (supplier selection)

In general, vendor assessment and supplier selection can be sequentially separated into three steps: (1) determining the importance weights of evaluation criteria, (2) deriving the performance scores for the competing alternatives, and (3) sorting the competing suppliers according to the importance weights and performance scores (Chen et al., 2006; Araz and Ozkarahan, 2007; Chai et al., 2013). In order to make a compromise decision among the conflicting criteria or multiple objectives (Erol et al., 2003; Kumar et al., 2004; Lin et al., 2010), evaluators usually adopt the MCDM (*multi-criteria decision making*) based schemes that consists of MADM (*multi-attribute decision making*) and MODM (*multi-objective decision making*). Typical MCDM methods for conducting the task of supplier selection include AHP (analytical hierarchy process), ANP (analytical network process), DEA (data envelopment analysis), mathematical (goal) programming, ELECTRE (ELimination Et Choix Traduisant the REality), PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluation), GRA (Grey Relational Analysis), and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution).

Although AHP and ANP are good at deriving the importance weights of evaluation criteria, both of them require significant computation complexities to complete pairwise comparisons. Specifically, the AHP is by nature limited to the assumption of independent criteria while the ANP can accommodate the interdependent criteria. Unlike the widely adopted AHP or ANP, ELECTRE, PROMETHEE, GRA, TOPSIS, and VIKOR are usually used for ranking the competitive suppliers (Ho et al., 2010; Chai et al., 2013; Tsai and Chou, 2009; Tsai, 2014; Shaik and Abdul-Kader, 2014). In this study, rather than deriving an overall ranking index, the relative strengths and weaknesses among the competitive vendors are visualized and displayed in terms of MRs and TAs.

2.2 Product (supplier) recommendation

The benefits of product recommendation include increasing the probability of cross-selling, consolidating customer loyalties, fulfilling customer retention or acquisition, and attracting potential customers (Liu and Shih 2005). Despite rapid advances in data mining technologies significantly improve the performances of recommender systems, they are usually dependent on customer purchase history or transaction records to predict customers' future desires and buying intentions (Adomavicious and Tuzhilin, 2005). In general, recommender systems are classified into three categories: (1) content-based filtering (CB): respondents are recommended items similar to the ones they preferred in the past, (2) collaborative filtering (CF):

respondents are recommended items that people with similar tastes and preferences, and (3) hybrid models: these methods combine the above-mentioned two approaches.

Obviously, most of the conventional schemes conduct product recommendation in a supervised way and thus they are weak in handling a scenario in which customer buying profiles are insufficient or unavailable (i.e. *new customers do not have experiences or records in buying or using BI packages*). When a new product is initially introduced or launched into the market, it's very difficult to gather sufficient training samples to construct intelligent recommender systems (Bobadilla et al., 2013). In other words, when users are given to the yet unseen items, preference-based filtering needs to be developed to capture and predict the preferences of respondents. Sometimes, this approach focuses on the relative order of alternatives (ranking based), rather than their absolute scores (rating based). In this study, fuzzy AHP is adopted to capture respondents' relative preferences for MRs and then supplier recommendation can be realized in an unsupervised way.

Despite numerous publications have been presented to address the aforementioned issues, however, most of them have the following demerits: (1) vendor assessment does not consider the dependences between MRs and TAs and (2) product recommendation is often conducted by constructing a supervised recommender system. Hence, an unsupervised scenario in which users' transaction records do not exist in the database cannot be well accommodated.

3. The proposed framework

As it was mentioned earlier, evaluation criteria for assessing BI solution vendors are separated into two aspects, including marketing requirements (voice of customers) and technical attributes (voice of engineering). Thus, the framework of QFD is adopted in this study. In order to accommodate human linguistic properties (see Table 3), fuzzy MCDM schemes are incorporated into the conventional QFD and details of the presented framework are described as follows (see Fig. 4 and Table 2):

- Initially, the QFD is employed to separate evaluation criteria into marketing requirements (voice of customers) and technical attributes (voice of engineering),
- Then, fuzzy DEMATEL is used to derive the dependences between MRs and TAs and the correlations among themselves for deriving the importance weights,
- Meanwhile, fuzzy Delphi is used to derive the performance scores (measured in terms of TAs) of the benchmarking vendors for better visualization,
- Finally, fuzzy AHP is employed to capture user preferences for MRs for recommending optimally fit BI systems.

[Fig. 4. Here]

[Table 2 Here]

3.1 Using fuzzy DEMATEL to identify the dependences of TAs on MRs

DEMATEL (*decision making trial and evaluation laboratory*), developed by the science and human affairs program of the Battelle Memorial Institute of Geneva Research Centre (Fontela and Gabus, 1976; Jeng and Tzeng, 2012; Tsai et al., 2013a; 2013b; 2013c), is able to visualize the interdependent relationships (causality) of the whole system. Suppose p experts are invited to assess m marketing requirements (MRs) and n technical attributes (TAs), the details of fuzzy DEMATEL are described as follows (see Fig. 5):

- Assigning a fuzzy rating scale to measure the direct-relation matrix:

  As seen in Table 2, a $(m+n)\times(m+n)$ fuzzy matrix $\tilde{X}$ with an element of $\tilde{x}_{ij}{}^{k} = (l_{ij}{}^{k}, m_{ij}{}^{k}, u_{ij}{}^{k})$ is evaluated by expert k, which represents the impact of TA_j on CR_i and all the diagonal elements of matrix $\tilde{X}$ will be set as zero ($\tilde{x}_{ii}{}^{k} = (0,0,0)$). After averaging all experts' scores, the direct-relation matrix $\tilde{A}$ is characterized with an element of $\tilde{a}_{ij}$:

$$\tilde{a}_{ij} = \frac{1}{S}\sum_{k=1}^{S}\tilde{x}_{ij}{}^{k} = (al_{ij}, am_{ij}, au_{ij}) \tag{3}$$

- Normalizing the direct-relation matrix:

  The normalized matrix $\tilde{B}$ can be obtained by normalizing the matrix $\tilde{A}$:

$$\tilde{b}_{ij} = \frac{1}{\Omega}\tilde{a}_{ij} = (bl_{ij}, bm_{ij}, bu_{ij}) \text{, where} \tag{4}$$

$$\Omega = Max\left(\max_{1\le i\le n}\sum_{j=1}^{n}u_{ij}, \max_{1\le j\le n}\sum_{i=1}^{n}u_{ij}\right) \tag{5}$$

- Deriving the total-relation matrix:

Once the normalized matrix $\tilde{B}$ has been obtained, the total-relation matrix $\tilde{T}$ can be derived based on Eq. (6) - Eq. (9):

$$\tilde{T} = \tilde{B} + \tilde{B}^2 + \tilde{B}^3 + \cdots = \tilde{B}(I - \tilde{B})^{-1}, \tag{6}$$

where $\tilde{t}_{ij} = (tl_{ij}, tm_{ij}, tu_{ij})$ and the amount of three matrix elements are list below:

$$matrix[tl_{ij}] = B_l(I - B_l)^{-1}, \tag{7}$$

$$matrix[tm_{ij}] = B_m(I - B_m)^{-1}, \tag{8}$$

$$matrix[tu_{ij}] = B_u(I - B_u)^{-1}, \tag{9}$$

where I denotes an identity matrix and $B_l/B_m/B_u$ represents the crisp matrix composed of the lower/medium/upper values of the normalized matrix.

- Defuzzifying the total-relation matrix $\tilde{T}$ and computing a causal diagram through the dispatcher group D and the receiver group R, where D is the sum of rows in crisp matrix T and R is the sum of columns:

$$T_{ij} = \frac{tl_{ij} + tm_{ij} + tu_{ij}}{3}, \tag{10}$$

After a crisp matrix T is obtained via Eq. (10), the dependences between MRs and TAs (R_{ij}') and the correlations among themselves ($\lambda_{ik} / \gamma_{kj}$) will be automatically extracted from the matrix T.

- Visualizing the causal diagram inherent the entire system by displaying the dataset composed of (D+R, D-R):

$$D_i = \sum_{j=1}^{n} T_{ij}, \tag{11}$$

$$R_j = \sum_{i=1}^{n} T_{ij} \tag{12}$$

It is noted that *D* represents "dispatcher" and *R* means "receiver". Specifically, the horizontal axis "*D+R*" named "*prominence*" reveals how much importance the criterion is. In contrast, the vertical axis "*D-R*" named "*influence*" distinguishes the criterion between the cause group (positive influence) and the effect group (negative influence). Following Chang and Cheng (2011), the importance weights of TAs and MRs are simply obtained through normalizing their absolute influence scores:

$$Wt_j = \left|D_j - R_j\right| \Big/ \sum_j \left|D_j - R_j\right|, \tag{13}$$

where D_j - R_j stands for a signed influence score for criterion *j*.

[Fig. 5. Here]

3.2 Using fuzzy Delphi method to determine the performance scores of BI vendors

Delphi method has been commonly adopted as a group-decision based forecasting technique. Normally, it requires a group of partially or completely anonymous experts responding their opinions on the preset questionnaires and involves several rounds of iterations to reach a consensus. In simple words, all experts respond to the questionnaire and the results are evaluated and then returned to experts through a feedback process. In reality, Delphi method often suffers from low convergence among the invited experts, high execution cost and tedious operating process. Besides, because linguistic human judgments are usually imprecise, evaluation terms expressed in fuzzy sense might be more feasible in practice. Thus, Murry et al. (1985) suggested incorporating the concept of fuzzy set into the conventional Delphi to fast reach a consensus among experts' opinions. Following Wang and Chen (2012), fuzzy Delphi method is slightly modified to generate the performance scores for BI vendors (in terms of TAs). The process is described below:

- The domain experts are invited to assess the performance scores of competing BI vendors (with respect to TAs). In particular, the rating scale is measured in terms of a triangular fuzzy number as:

  $$\tilde{S}_i = (S_{ia}, S_{ib}, S_{ic}), \quad 1 \le i \le p, \tag{14}$$

  where p represents the number of evaluators, n denotes the number of attributes, and $\tilde{S}_i$ is the performance score of an attribute assigned by evaluator i.

- Aggregating the performance scores among the experts to attain an average:

  $$\tilde{S}_m = \frac{1}{p}\left(\sum_{i=1}^{p} S_{ia}, \sum_{i=1}^{p} S_{ib}, \sum_{i=1}^{p} S_{ic}\right) = (S_{ma}, S_{mb}, S_{mc}), \tag{15}$$

  Here, the differences between $\tilde{S}_i$ and $\tilde{S}_m$ are calculated and sent back to the evaluators for reconsidering their original assessments.

- For the later rounds, all evaluators are required to revise their fuzzy rating and the process is similarly repeated until the gaps between the successive means are reasonably converged. To calculate the distance between two fuzzy numbers, the following is adopted (Geng et al., 2010):

$$d(\tilde{S}_m{}^t, \tilde{S}_m{}^{t+1}) = \frac{1}{\sqrt{3}}\left[\sqrt{(S_{ma}{}^t - S_{ma}{}^{t+1})^2 + (S_{mb}{}^t - S_{mb}{}^{t+1})^2 + (S_{mc}{}^t - S_{mc}{}^{t+1})^2}\right], \quad (16)$$

where $\tilde{S}_m{}^t / \tilde{S}_m{}^{t+1}$ represents a fuzzy mean at iteration *t*/*t*+1.

- Based on "the center of area" approach, the process of defuzzification is applied to convert a fuzzy performance rating into a crisp value:

$$S_m = \frac{S_{ma} + S_{mb} + S_{mc}}{3}, \quad (17)$$

Here, it is noted that the performance scores for the competing BI vendors are measured in terms of TAs. To further associated performances in terms of MRs, Eq. (3) needs to be applied for displaying a radar plot.

3.3 Using fuzzy AHP to user preferences for MRs

AHP (analytic hierarchy process) was originally proposed by Saaty (1980) back in the early 1970s in response to the allocation of scarce resources for the military. Generally, the AHP requires decision makers (domain experts) to carry out pairwise comparisons between criteria or among alternatives, then employing eigenvalue computation to derive the weights of criteria and the priorities of alternatives. The original AHP is developed in a crisp manner and performed on a hierarchical structure. Following Wang and Wu (2014), fuzzy AHP is adopted to accommodate the linguistic property of human judgments.

- Employing pairwise comparisons between n criteria (alternatives). Based on triangular fuzzy numbers, a five-point linguistic scale is recommended to express experts' preferences between two criteria, such as equally, slightly, moderately, strongly, and extremely preferred (see Table 3 again),

- Aggregating all experts' judgments. Suppose S experts are invited to assess n criteria and let expert k be an illustrated example. The relative importance of criterion i over criterion j can be expressed by the following fuzzy matrix:

$$S_k = \begin{bmatrix} \tilde{b}_{11k} & \tilde{b}_{12k} & \cdots & \tilde{b}_{1nk} \\ \tilde{b}_{21k} & \tilde{b}_{22k} & \cdots & \tilde{b}_{2nk} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{b}_{n1k} & \tilde{b}_{n2k} & \cdots & \tilde{b}_{nnk} \end{bmatrix}, \quad k = 1,2,\cdots S, \tag{18}$$

where $\tilde{b}_{ijk}$ represents the relative importance of criterion i over criterion j assessed by expert k. All experts' results are aggregated through (19) - (21):

$$\tilde{b}_{ij} = (L_{ij}, M_{ij}, U_{ij}), \quad i = 1,2,\cdots n, \quad j = 1,2,\cdots n, \quad k = 1,2,\cdots S \tag{19}$$

$$L_{ij} = \min(b_{ijk}), \quad M_{ij} = \sum_{k=1}^{S} b_{ijk} / S, \quad U_{ij} = \max(b_{ijk}) \tag{20}$$

$$b_{ij} = (L_{ij} + M_{ij} + U_{ij}) / 3, \tag{21}$$

where $\tilde{b}_{ij}$ denotes an aggregated fuzzy number and b_{ij} represents a defuzzified value (Chua and Lin 2009; Lin *et al.* 2010),

- Computing the maximum eigenvalues and eigenvectors in order to estimate the relative weights of n criteria. The derivation process is shown below:

$$A = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix} \quad (22)$$

$$AW = \lambda_{\max} W \, , \quad (23)$$

where A means the $n \times n$ pairwise comparison matrix between n criteria, $\lambda_{\max}$ is the largest eigenvalue of A and W means its corresponding eigenvector.

- Checking the consistency of the matrix. The decision quality is related to the consistency of judgments that decision makers demonstrated during the process of pairwise comparisons. The consistency index (*CI*) and consistency ratio (*CR*) are defined to determine the consistency of decision quality:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \, , \quad (24)$$

$$CR = \frac{CI}{RI} \, , \quad (25)$$

where *CI* measures the inconsistency (the closer to zero, the greater the consistency) and *RI* represents a random index (see Table 4). When the CR exceeds 0.1, it indicates the decision process may be inconsistent and decision makers are asked to revise their judgments.

4. An illustrated example

Referring to Fig. 2 again, the top five BI vendors are sequentially listed as SAP, Oracle, SAS, IBM, and Microsoft (Ravi, 2012). By considering the status of Taiwan's most companies, three vendors including SAP, SAS, and Microsoft are selected to conduct vendor assessment. After consulting IT experts, evaluation criteria composed of five MRs and twelve TAs is demonstrated in Table 4. In order to enhance the reliability of this survey, more than half questionnaires were sent to the IT/MIS officers or executives who work in the Hsinchu science park. The remaining half was sent to consult main user groups like financial analysts, marketing planners, and general managers.

[Table 4 Here]

4.1 Using QFD to identify the interdependences between MRs and TAs

Initially, fuzzy DEMATEL (see Fig. 5 again) is incorporated into the framework of the QFD. By using a five-point fuzzy scale (i.e. *1-very low, 2-low, 3-medium, 4-high, and 5-very high*), the invited respondents are required to complete the following question (see Table 5): *How do you measure the impacts of TAs on MRs and the correlations among them?* After aggregating the results of the respondents, the total-relation matrix can be derived via Eqs. (4) – (11). Then, based on Eqs. (12) – (13), a causal diagram to describe the interdependences between MRs and TAs is displayed in Fig. 6 (also see Table 6). Apparently, all of the TAs (denoted by the "*square*") is acting as the "cause" (dispatcher) group because of positive influence. In contrast, due to having negative influence, all of the MRs (denoted by the "*diamond*") is classified into the "effect" (receiver) group. This plot can help software planners visualize the underlying dependences between TAs and MRs.

Here, the absolute "influence" score is used to generate the importance weights of MRs and TAs (see Eq. (14)). Referring to Table 6 again, the top priorities of MRs which are ranked as $R3 \succ R5 \succ R2$ include business analytics & simulation, data mining & statistics, and business query & reporting. Similarly, the significant TAs are sequentially prioritized as $A2 \succ A11 \succ A1$ which indicates data visualization, feature extraction & selection, and ETL (extraction/transformation/loading) are perceived relatively important in the minds of BI users. By combining QFD with fuzzy DEMATEL, software planners can understand which MRs are really concerned and how to effectively improve them through specific TAs.

[Fig. 6. Here]

[Table 5 – Table 6 Here]

4.2 Conducting vendor assessment and supplier recommendation

In order to conduct vendor assessment for the competitive BI vendors, fuzzy Delphi is employed to fast reach a consensus. Specifically, the following question- "*how do you assess the performances of the competing BI vendors in terms of TAs*?"

is applied to the experienced IT experts. Based on the total-relation matrix extracted in fuzzy DEMATEL, the interdependences between MRs and DAs shown in Table 7 are used to derive the performance scores of BI vendors in terms of MRs (see Eqs. (1) – (2)). Intuitively, the stronger dependences between R_i and A_j also imply the greater impacts of A_j on R_i. For convenience, the aggregated performance scores measured in terms of MRs and TAs are listed in Table 8. For better visualization, both types of the performance scores are portrayed in Fig. 7 (a line plot with regard to TAs) and Fig. 8 (a radar plot with respect to MRs), respectively. Obviously, each vendor has its relative weaknesses. For instance, SAP is deficient in R1 and R5, SAS is weak in R1, and R4, and Microsoft is in R1. Not surprisingly, the aspect of "human-computer interface" (R1) is perceived unsatisfactorily for all of the benchmarking vendors.

Lastly, with the aid of fuzzy AHP, the following question- "*how much importance is R_i preferred to R_j?*" is employed to capture user preferences for MRs. Based on calculating the Cosine similarity between user preferences and vendors' performance scores, supplier recommendation is conducted in an unsupervised way. Table 9 briefly describes the results for three distinct users. In simple words, the profiles of user preferences are mapping with a specific BI vendor that preforms relatively excellently in associated MRs. Very interestingly, Microsoft's market share is minimal (10.7%) although it is perceived to be weak in only R1. Not surprisingly, SAP is promoting BI solutions to its existing ERP users. In contrast, SAS originated from the statistics community recently switch into the area of BI. In the future, we presume that Microsoft will exert significant resources to integrate its database system, data warehousing, with data mining packages (including statistical modules) for enlarging its market share.

[Fig. 7. – Fig. 8. Here]

[Table 7 – Table 9 Here]

5. Conclusions

Today, business analytics and business intelligence has become a popular enterprise information system to significantly improve information quality and decision timeliness. Typical BI users involve financial analysts, marketing planners, and general managers. Unfortunately, most of them may not have sufficient IT backgrounds. In order to help these users communicate with MIS executives, this study presents a systematic framework to connect marketing requirements with technical attributes. In the context, the entire process is sequentially separated into vendor assessment (phase 1) and product recommendation (phase 2). In this paper, fuzzy MCDM schemes are appropriately fused into the QFD framework and the main contribution of this paper are highlighted as follows:

- *The importance weights of MRs and TAs are systematically derived (via fuzzy DEMATEL) after considering the causal interdependences between them,*
- *The performance scores (in terms of MRs and DAs) of BI vendors are efficiently generated (via fuzzy Delphi) for accomplishing supplier benchmarking,*
- *User preferences for MRs are effectively captured (via fuzzy AHP) to conduct product recommendation of BI software in an unsupervised manner.*

Based on experimental results, it is found that three surveyed BI vendors are concurrently unsatisfactory in "human-computer interface". Besides, SAS is deficient in "database & data warehousing" while SAP is perceived weak in "data mining & statistics". However, the market shares of three suppliers are sequentially ranked as SAP (22%), SAS (13%), and Microsoft (11%) although Microsoft is perceived as the most satisfactory in terms of market requirements. As we know, SAP already owns a huge market base in the ERP (enterprise resource planning) field. In contrast, SAS is a well-known statistics package provider and Microsoft is the dominant player in the operating systems of personal computers. Obviously, these findings provide a directional guide for global firms to improve their future commercial BI systems.

In this study, research limitation is stated as follows. Supplier recommendation is conducted and based on user preferences. However, this approach cannot take the network effect between installed ERP systems and selecting BI software into account. Nevertheless, without incurring computational complexity, this study presents an integrated framework to help chief information officers or corporate executives fast evaluate competitive BI vendors and select their best-fit solutions. In future work, critical success factors or other economic benefits for implementing business intelligence systems deserve to be further addressed.

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Table 1. An overall comparison among various information technologies

	Database system	Data warehousing	Data mining	Business intelligence
Main objectives	On-line transaction processing	On-line analytical processing	Knowledge discovery	Decision support
Core techniques	Relational database, normalization	Star schema, snowflake schema, data mart	Association, clustering, classification	Data warehousing, data mining, data visualization
Strengths	Transaction data, data storage	Historical data, *ad-hoc* queries	Big data, data analysis	Performance management
Limitations	Low speed, data irregularity, and security	Cost of extraction, transformation, and loading	Variety of data and high dimensionality	Identifying causality between predictors and outcomes

Table 2. The linguistic rating scale used in fuzzy schemes

Fuzzy number	Fuzzy DEMATEL (causality measure)	Fuzzy Delphi (performance measure)	Fuzzy AHP (preference measure)
$\tilde{1}$ (0, 0, 2)	L (slightly)	L (slightly)	E (equally)
$\tilde{3}$ (1, 3, 5)	W (weakly)	W (weakly)	W (weakly)
$\tilde{5}$ (3, 5, 7)	M (moderately)	M (moderately)	M (moderately)
$\tilde{7}$ (5, 7, 9)	S (strongly)	S (strongly)	S (strongly)
$\tilde{9}$ (8, 10, 10)	X (extremely)	X (extremely)	X (extremely)

Table 3. A random index used in fuzzy AHP

	Order of matrix						
n	2	3	4	5	6	7	8
RI	0	0.58	0.90	1.12	1.24	1.32	1.41

Table 4. An illustration of MRs and TAs for assessing BI vendors

MRs	Marketing requirements	TAs	Technical attributes
R1	Human-computer interface	A1	ETL (extraction, transformation, loading)
R2	Business query & reporting	A2	Data visualization (dashboard & scorecards)
R3	Business analytics & simulation	A3	Database compatibility & integrity
R4	Database & data warehousing	A4	Database maintenance & recovery
R5	Data mining & statistics	A5	Performance monitoring & management
		A6	Statistical regression
		A7	Temporal forecasting
		A8	Affinity association
		A9	Unsupervised clustering
		A10	Supervised classification
		A11	Feature extraction & selection
		A12	Causality reasoning & corporate diagnoses

Table 5. An illustrated fuzzy MCDM questionnaire

Fuzzy Schemes	Corresponding questions	Objectives
Fuzzy DEMATEL	● *How much influence does attribute A_i exert on attribute A_j?* ● *How much influence does attribute A_i exert on requirement R_j?*	Causality relationships
Fuzzy Delphi	● *How much performance is the vendor perceived* with respect to *attribute A_i?*	Performance scores
Fuzzy AHP	● *How much importance is requirement R_i preferred to requirement R_j* for a specific *user*?	User preferences

Table 6. Using fuzzy DEMATEL to visualize a diagram between MRs and TAs

	Active score D_i	Passive score R_j	Prominence score $D_i + R_j$	Influence score $D_i - R_j$	Importance weights
R1		0.580	0.580	-0.580	0.131
R2		0.910	0.910	-0.910	0.205
R3		1.166	1.166	-1.166	0.263
R4		0.694	0.694	-0.694	0.156
R5		1.086	1.086	-1.086	0.245
A1	0.711	0.191	0.902	0.520	0.117
A2	0.831	0.044	0.875	0.788	0.178
A3	0.543	0.155	0.698	0.388	0.088
A4	0.354	0.228	0.582	0.126	0.028
A5	0.687	0.351	1.037	0.336	0.076
A6	0.366	0.073	0.439	0.293	0.066
A7	0.366	0.073	0.439	0.293	0.066
A8	0.334	0.073	0.406	0.261	0.059
A9	0.301	0.073	0.374	0.228	0.051
A10	0.334	0.073	0.406	0.261	0.059
A11	0.819	0.131	0.950	0.689	0.155
A12	0.669	0.413	1.083	0.256	0.058

Table 7. The dependences between MRs and TAs

	R1	R2	R3	R4	R5
A1		0.148		0.303	
A2	0.288	0.133	0.143		0.005
A3		0.177		0.172	
A4		0.015		0.219	
A5	0.139	0.166	0.184		0.027
A6	0.007	0.010	0.113		0.162
A7	0.007	0.010	0.113		0.162
A8	0.007	0.074	0.016		0.162
A9	0.007	0.010	0.081		0.129
A10	0.007	0.010	0.081		0.162
A11	0.002	0.007	0.187		0.276
A12	0.115	0.150	0.250		0.003

Table 8. The performance scores measured in terms of MRs and TAs

MRs	SAP	SAS	Microsoft	TAs	SAP	SAS	Microsoft
R1	4.776	3.318	3.975	A1	6.9	4.6	8.7
R2	6.690	5.051	6.661	A2	9.4	6.1	7.7
R3	6.867	7.569	7.469	A3	7.8	5.9	8.6
R4	5.447	3.350	5.824	A4	9.2	4.3	7.8
R5	4.709	8.209	7.265	A5	8.6	5.7	6.4
				A6	5.3	8.8	6.4
				A7	4.3	8.4	6.6
				A8	4.7	6.8	7.2
				A9	4.9	7.9	7.2
				A10	4.6	6.9	7.8
				A11	2.6	7.2	5.7
				A12	6.1	4.2	5.3

Table 9. Supplier recommendation based on users' preferences

Preferences	User 1	User 2	User 3
R1	0.11	0.15	0.09
R2	0.21	0.1	0.25
R3	0.32	0.33	0.28
R4	0.26	0.15	0.17
R5	0.1	0.27	0.21
Recommendation	SAP	SAS	Microsoft

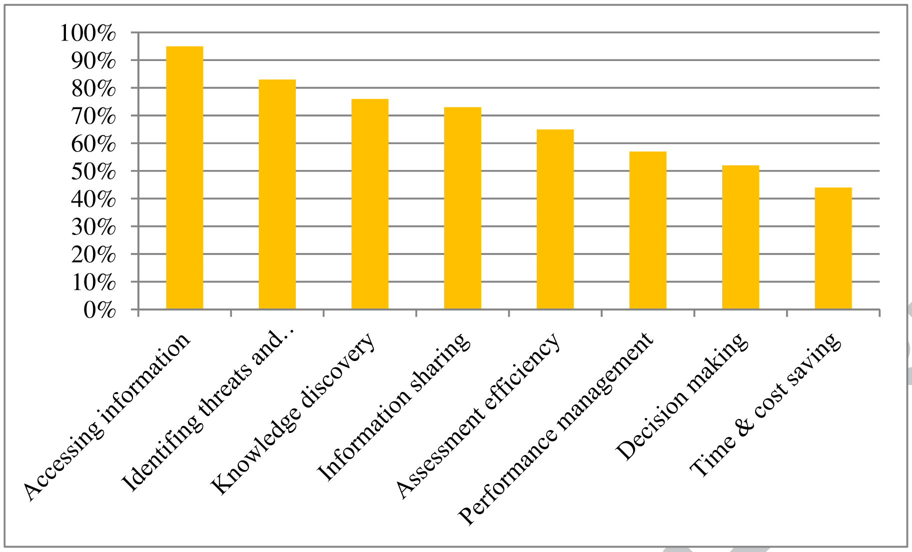

Fig. 1. The benefit items of business intelligence

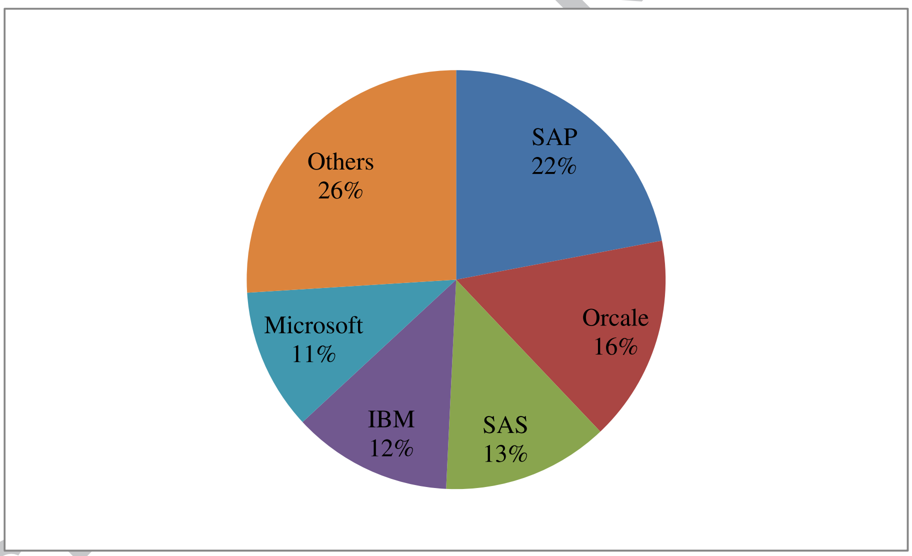

Fig. 2 The key players in the BI market

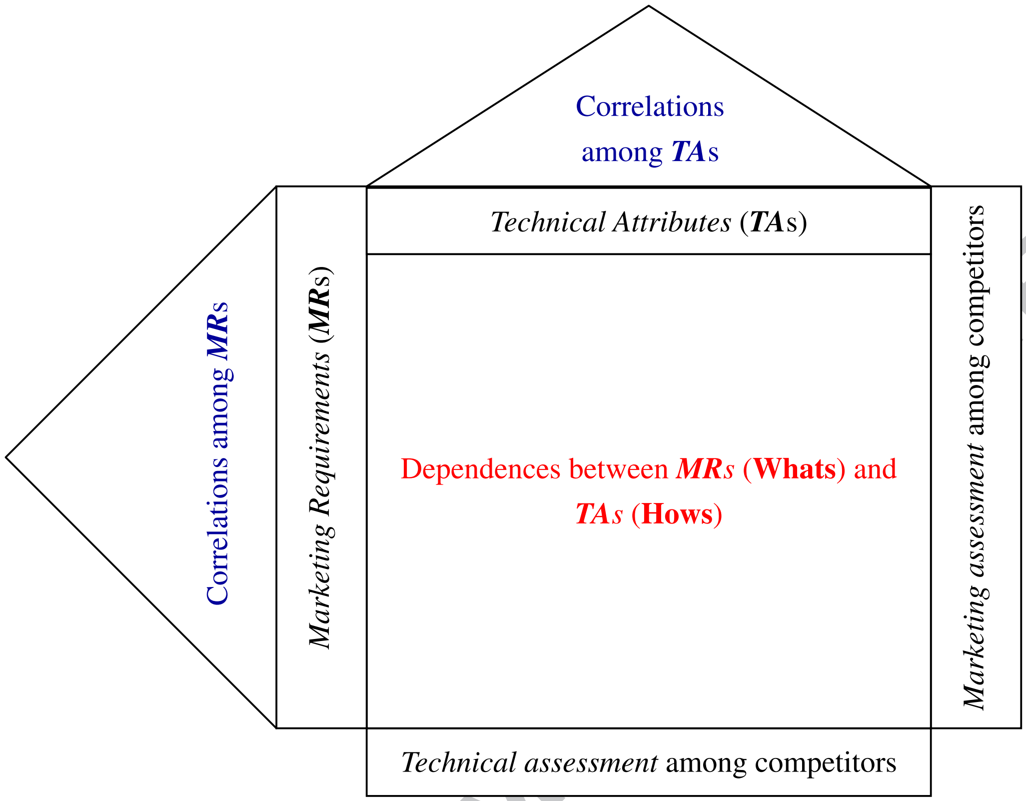

Fig. 3. The conventional QFD

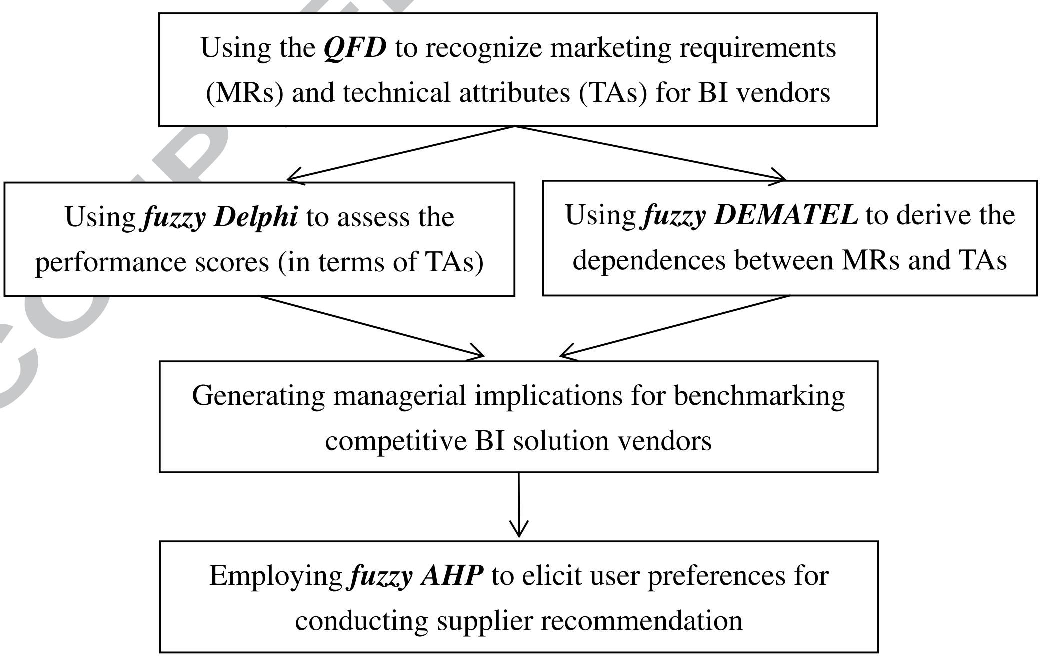

Fig. 4. The proposed framework

	CR_1 . . . . CR_m	TA_1 . . . . TA_n
CR_1 . CR_m	$m \times m$ correlation matrix	$m \times n$ zero matrix
TA_1 . TA_n	$n \times m$ dependence matrix	$n \times n$ correlation matrix

Fig. 5. Input to the direct-relation matrix for fuzzy DEMATEL

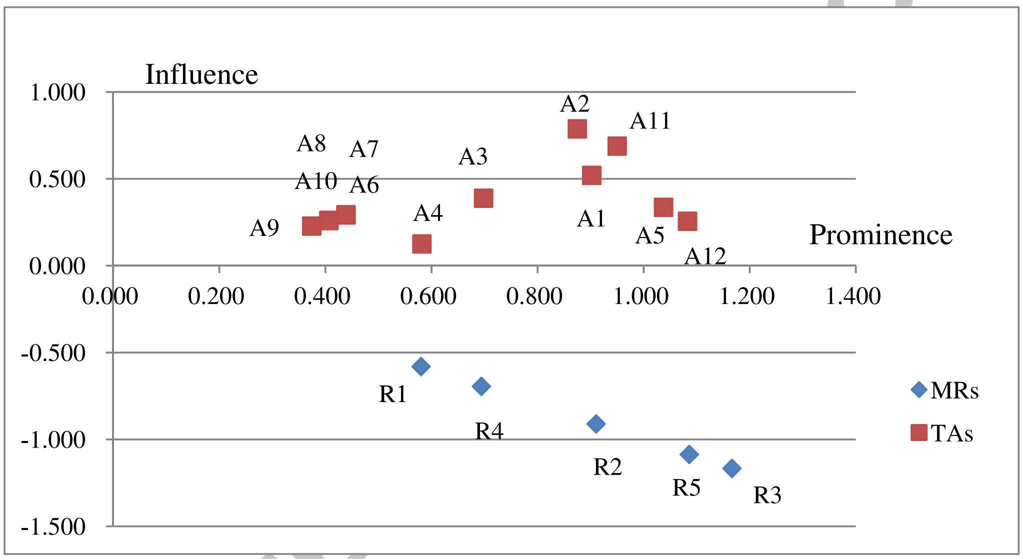

Fig. 6. A causal diagram between MRs and TAs

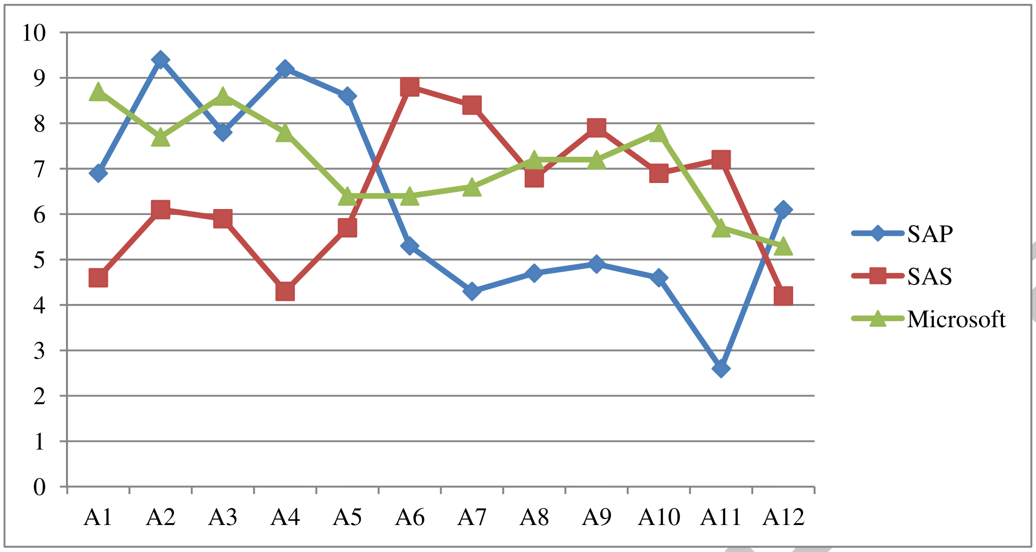

Fig. 7. A line diagram measured in terms of TAs

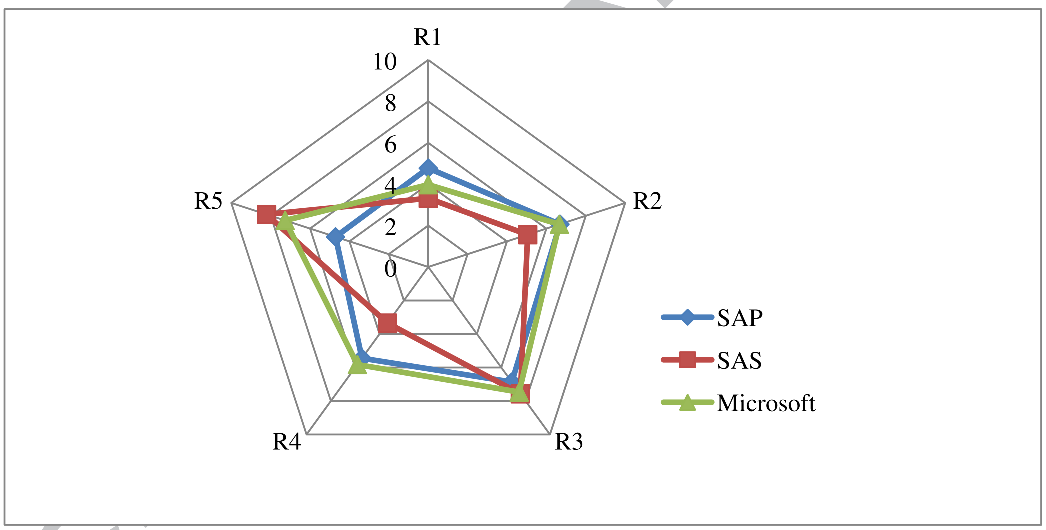

Fig. 8. A radar diagram measured in terms of MRs

Highlights

- A QFD (quality function deployment) based framework is presented,
- Evaluation criteria consist of marketing requirements and technical attributes,
- Various fuzzy MCDM (multi-criteria decision making) schemes are fused,
- Vendor assessment and supplier recommendation are accomplished,
- Supplier recommendation is conducted in an unsupervised way,
- The competitive BI (business intelligence) vendors are visualized to generate managerial insights.