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Developing global managers' competencies using the fuzzy DEMATEL method

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Abstract

Modern global managers are required to possess a set of competencies or multiple intelligences in order to meet pressing business challenges. Hence, expanding global managers' competencies is becoming an important issue. Many scholars and specialists have proposed various competency models containing a list of required competencies. But it is hard for someone to master a broad set of competencies at the same time. Here arises an imperative issue on how to enrich global managers' competencies by way of segmenting a set of competencies into some portions in order to facilitate competency development with a stepwise mode. To solve this issue involving the vagueness of human judgments, we have proposed an effective method combining fuzzy logic and Decision Making Trial and Evaluation Laboratory (DEMATEL) to segment required competencies for better promoting the competency development of global managers. Additionally, an empirical study is presented to illustrate the application of the proposed method.

Keywords: Global managers; Competency; Multiple intelligences; Decision Making Trial and Evaluation Laboratory (DEMATEL)

1. Introduction

In meeting the impact of existing and future globalization advancements, most companies have an ongoing need for competent global managers (Harvey, Novicevic, & Kiessling, 2002). Especially, the ability of organizations to effectively compete in the global marketplace is dependent on identifying and maintaining an adequate number of qualified global managers (Harvey & Richey, 2001; McKenna, 1998; Sinkovics, Bell, & Deans, 2004). To maintain an adequate staff of capable global managers, companies must effectively enforce global manager selection with multiple intelligences as specific competencies (Harvey & Richey, 2001; Harvey et al., 2002), and help global managers to identify and cultivate their competencies. It is now a leading company strategy to apply competency models to help global managers to develop their competencies.

The competency model is a set of competencies, namely success factors which include the key behaviors required for excellent performance in a particular role (Schoonover, Schoonover, Nemerov, & Ehly, 2000). In addition, the competency model can be used to identify the competencies which employees need to improve performance in their current job or to prepare for other jobs (Sinnott, Madison, & Pataki, 2002). Several surveys report that numerous modern enterprises are progressively adopting competency models as essential management technologies to enhance their competitiveness (JPC-SED, 2002; Schoonover et al., 2000). There are several useful manager competency models, such as: Boyatzis (1982), Hellriegel, Jackson, and Slocum (2002), Quinn, Faerman, Thompson, and McGrath (1996), and Spencer and Spencer (1993). However, each of these competency models contains too many competencies. It is hard for someone to master a broad set of competencies simultaneously. In order to be smart for

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launching competency applications effectively, it is a favorable way that focusing on some urgent competencies and implementing them with a stepwise mode (Wu, Lee, & Tzeng, 2005). Thus here arises the imperative issue of how to enrich global manager competencies by way of segmenting a set of competencies into some portions in order to effectively facilitate competency development. Unfortunately, few works discuss this issue.

To solve this issue, it is suitable to use the Decision Making Trial and Evaluation Laboratory (DEMATEL). The DEMATEL method (Gabus & Fontela, 1972, 1973) is a potent method that helps in gathering group knowledge for forming a structural model, as well as in visualizing the causal relationship of sub-systems through a causal diagram. However, in many cases, the judgments of decision-making are often given as crisp values, but crisp values are an inadequate reflection of the vagueness of the real world (Bellman & Zadeh, 1970; Zadeh, 1965). The fact that human judgment about preferences are often unclear and hard to estimate by exact numerical values, so that fuzzy logic is necessary for handling problems characterized by vagueness and imprecision (Chang, Yeh, & Cheng, 1998; Chen & Chiou, 1999). Hence, there has a need to extend the DEMATEL method with fuzzy logic for making better decisions in fuzzy environments.

Therefore, the aim of this paper is to develop the fuzzy DEMATEL method to segment required competencies for better promoting the competency development of global managers. Also, an empirical study of a high-tech company is presented as a test case to illustrate our proposed method and to demonstrate its usefulness. The rest of this paper is organized as follows. In Section 2, some of the prior literature relating to competencies and multiple intelligences is reviewed. In Section 3, the proposed method is described. In Section 4, an empirical study is illustrated. Finally, according to the findings of this research, conclusions and suggestions are presented.

2. From competencies towards multiple intelligences

Successfully managing the challenges of globalization, companies need to possess enough capable global managers. For assessing a competent global manager, there has been a new shift away from the competency approach towards the multiple intelligences approach. Hence, competencies and multiple intelligences are discussed below.

2.1. Competencies and competency models

In view of the knowledge-based nature of competition, global managers need a broad range of managerial competencies. Especially, successful global management will think strategically in a worldwide context, but act like a local organization in each national market (Sheridan, 1997). According to McKenna (1998), identifying management competencies would enable managers to perform more effectively, and lead to develop the dimensions of effective management and leadership behavior. Moreover, Rosen and Digh (2001) indicate that global manager competencies are the new leadership competencies required for business success in today's multicultural and global economy.

The concept of competency has been developed by McClelland and the McBer and Company in 1970s. Especially, McClelland's paper, "Testing for Competence rather than Intelligence" (McClelland, 1973), started the competency movement in the 1970s. Schoonover et al. (2000) remark that competencies provide significant help with key problems such as: clarifying workforce standards and expectations; and aligning individuals with the organization's business strategies. Generally, competencies are characteristics of people that differentiate performance in a specific job or role (Kelner, 2001; McClelland, 1973). Now competencies are commonly conceptualized as a measurable pattern of knowledge, skills, abilities, behaviors, and other characteristics (KSAOs) that differentiate high from average performance (Athey & Orth, 1999; Mirable, 1997; Rodriguez, Patel, Bright, Gregory, & Gowing, 2002). Regarding the notion of a competency model, Mansfield (1996) states that a competency model is a detailed description of behaviors and abilities which employees are required to have to be effective in a job. The competency model is useful to identify capabilities and attributes needed to meet current and future staffing needs, and to focus employee development efforts to eliminate the gap between capabilities needed and those available (Sinnott et al., 2002).

There are several notable manager competency models. Typically, Boyatzis (1982) suggests six clusters: goal and action management; leadership; human resource; directing subordinates; focus on others; and specialized knowledge. Moreover, Quinn et al. (1996) have grouped manager competency into eight clusters: mentor, facilitator, monitor, coordinator, director, producer, broker, and innovator. Further, Hellriegel et al. (2002) have developed six clusters of managerial competencies: self-management; strategic action; global awareness; teamwork; planning and administration; and communication. However, note that the above competency models usually contain many detailed competencies in each cluster. Dive (2004) suggests that it is better to implement the competency model gradually and to avoid involving too many competencies at a time.

2.2. Multiple intelligences and eight IQs

Regarding multiple intelligences, Gardner (1983) defines seven intelligences that differ greatly from the traditional view which usually recognizes as verbal or computational intelligence. Gardner's seven intelligences are: logical–mathematical intelligence; linguistic intelligence; spatial intelligence; musical intelligence; bodily-kinesthetic intelligence; personal intelligences; and intrapersonal intelligence. Moreover, Sternberg (1997) stresses that multiple intelligences are effective in selecting individuals with different competencies, and categorizes multiple intelligences into three groups based on the Triarchic Theory (Sternberg, 1985). These three groups all are the key to managerial intelligence, including: analytical intelligence; practical intelligence; and creative intelligence (Sternberg, 1997).

Recently, several works (Harvey & Richey, 2001; Harvey et al., 2002) suggest that multiple intelligences can be used as specific competences for the selection of global managers, owing to the rising significance of emotional competence (Boyatzis, Goleman, & Rhee, 1999). Emotional intelligence is the capacity for recognizing and managing our own feelings and those of others (Goleman, 1998). Motional competence is a learned capability based on emotional intelligence that contributes to effective performance in all aspects of life and in multiple environments (Boyatzis et al., 1999). Harvey and Richey (2001) emphasize that eight IQs have been identified to illustrate the heterogeneity of potential capabilities which global managers may possess.

According to their works (Harvey & Richey, 2001; Harvey et al., 2002), those different IQs are: (1) cognitive IQ involving the ability to reason, learn, and think analytically; (2) emotional IQ involving the ability to use one's own affective state to tap the affective state of others to accomplish specific objectives; (3) political IQ involving the manager's ability to use formal and informal power to accomplish objectives; (4) cultural/social IQ involving the extent to which one is adequately socialized into the cultural/social difference among organizations; (5) organizational IQ involving the ability of a manager to have a detailed and accurate understanding of how two organizations operate functionally; (6) network IQ involving the ability to get things done when working with multiple interrelated organizational units; (7) innovative IQ involving the ability to be innovative in thinking and create novel ideas and solutions to problems; and (8) intuitive IQ involving the ability to have quick insights into how to solve problems or to address situations without past experience with that particular problem and without actively or formally processing information. As per the above, there has been a recent shift away from the competency approach towards the multiple intelligences approach.

3. The fuzzy DEMATEL method

DEMATEL is a comprehensive method for building and analyzing a structural model involving causal relationships between complex factors. To lay the foundation for extending the DEMATEL method for making decisions in fuzzy environments, the essentials of the DEMATEL method and fuzzy logic are discussed below.

3.1. The DEMATEL method

The Battelle Memorial Institute conducted a DEMATEL method project through its Geneva Research Centre (Gabus & Fontela, 1972, 1973). The original DEMATEL was aimed at the fragmented and antagonistic phenomena of world societies and searched for integrated solutions. In recent years, the DEMATEL method has become very popular in Japan (Hori & Shimizu, 1999; Kamaike, 2001; Yamazaki et al., 1997; Yuzawa, 2002) because it is especially pragmatic to visualize the structure of complicated causal relationships.

Specifically, the DEMATEL method is based on digraphs, which can separate involved factors into cause group and effect group. Directed graphs, known as digraphs, are more useful than directionless graphs because digraphs can demonstrate the directed relationships of sub-systems. A digraph may typically represent a communication network, or some domination relation between individuals. Suppose a system contains a set of elements $S = \{s_1, s_2, \ldots, s_n\}$, and particular pair-wise relations are determined for modeling with respect to a mathematical relation R. Next, to portray the relation R as a direct-relation matrix that is indexed equally on both dimensions by elements from the set S. Then, except the case that the number is 0 appearing in the cell (i,j), if the entry is a positive integral that has the meaning of (1) the ordered pair (s_i, s_j) is in the relation R, and (2) there has the sort of relation regarding that element s_i causes element s_j.

The digraph portrays a basic concept of contextual relation among the elements of the system, in which the numeral represents the strength of influence. Hence, the DEMATEL method can convert the relationship between the causes and effects of factors into an intelligible structural model of the system. In order to apply the DEMATEL method smoothly, we refined the version used by Fontela and Gabus (1976) and make essential definitions as below.

Definition 1. The pair-wise comparison scale may be designated four levels, where the scores of 0, 1, 2, and 3 represent "No influence", "Low influence", "High influence", and "Very high influence" respectively.

Definition 2. The initial direct-relation matrix Z is a $n \times n$ matrix obtained by pair-wise comparisons in terms of influences and directions between criteria, in which z_{ij} is denoted as the degree to which the criterion i affects the criterion j, i.e., $Z = [z_{ij}]_{n \times n}$.

Definition 3. The normalized direct-relation matrix X, i.e., $X = [x_{ij}]_{n \times n}$ and $0 \leqslant x_{ij} \leqslant 1$ can be obtained through the formulas (1) and (2), in which all principal diagonal elements are equal to zero.

$$X = s \cdot Z, \tag{1}$$

$$s = \frac{1}{\max_{1 \leqslant i \leqslant n} \sum_{j=1}^{n} z_{ij}}, \quad i,j = 1,2,\ldots,n. \tag{2}$$

Definition 4. The total-relation matrix T can be acquired by using the formula (3), in which the I is denoted as the identity matrix.

$$T = X(I - X)^{-1}. \tag{3}$$

Definition 5. The sum of rows and the sum of columns are separately denoted as D and R within the total-relation matrix T through the formulas (4)–(6):

$$T = t_{ij}, \quad i,j = 1,2,\ldots,n, \tag{4}$$

$$D = \sum_{j=1}^{n} t_{ij}, \tag{5}$$

$$R = \sum_{i=1}^{n} t_{ij}, \tag{6}$$

where D and R denote the sum of rows and the sum of columns respectively.

Definition 6. A causal diagram can be acquired by mapping the dataset of $(D+R, D-R)$, where the horizontal axis $(D+R)$ is made by adding D to R, and the vertical axis $(D-R)$ is made by subtracting D from R.

3.2. The fuzzy logic

In the real world, many decisions involve imprecision since goals, constraints, and possible actions are not known precisely (Bellman & Zadeh, 1970). When making decisions in a fuzzy environment, the result of decision-making is highly affected by subjective judgments that are vague and imprecise. The sources of imprecision include: unquantifiable information, incomplete information, non-obtainable information, and partial ignorance (Chen, Hwang, & Hwang, 1992). To solve this kind of imprecision problem, fuzzy set theory was first introduced by Zadeh (1965) as a mathematical way to represent and handle vagueness in decision-making. In fuzzy logic, each number between 0 and 1 indicates a partial truth, whereas crisp sets correspond to binary logic: 0 or 1. Hence, fuzzy logic can express and handle vague or imprecise judgments mathematically (Al-Najjar & Alsyouf, 2003).

To deal with the vagueness of human thought and expression in making decisions, fuzzy set theory is very helpful. In particular, to tackle the ambiguities involved in the process of linguistic estimation, it is a beneficial way to convert these linguistic terms into fuzzy numbers. A linguistic variable is a variable whose values (namely linguistic values) have the form of phrases or sentences in a natural language (Von Altrock, 1996). The linguistic variable is very useful in dealing with situations which are described in quantitative expressions (Asan, Erhan Bozdag, & Polat, 2004; Delgado, Verdegay, & Vila, 1992). Especially, linguistic variables are used as variables whose values are not numbers but linguistic terms (Zadeh, 1975). The linguistic term approach is a convenient way for decision makers to express their assessments (Malaviya & Peters, 1997). In practice, linguistic values can be represented by fuzzy numbers, and the triangular fuzzy number is commonly used. In the following, we briefly review some essential definitions of fuzzy logic.

Definition 7. A fuzzy set $\widetilde{A}$ is a subset of a universe of discourse X, which is a set of ordered pairs and is characterized by a membership function $\mu_{\widetilde{A}}(x)$ representing a mapping $\mu_{\widetilde{A}} : X \to [0,1]$. The function value of $\mu_{\widetilde{A}}(x)$ for the fuzzy set $\widetilde{A}$ is called the membership value of x in $\widetilde{A}$, which represents the degree of truth that x is an element of the fuzzy set $\widetilde{A}$. It is assumed that $\mu_{\widetilde{A}}(x) \in [0,1]$, where $\mu_{\widetilde{A}}(x) = 1$ reveals that x completely belongs to $\widetilde{A}$, while $\mu_{\widetilde{A}}(x) = 0$ indicates that x does not belong to the fuzzy set $\widetilde{A}$.

$$\widetilde{A} = \{(x, \mu_{\widetilde{A}}(x))\}, \quad x \in X,$$

where $\mu_{\widetilde{A}}(x)$ is the membership function and $X = \{x\}$ represents a collection of elements x.

Definition 8. A fuzzy set $\widetilde{A}$ of the universe of discourse X is convex if

$$\mu_{\widetilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geqslant \min(\mu_{\widetilde{A}}(x_1), \mu_{\widetilde{A}}(x_2)) \quad \forall x \in [x_1, x_2],$$

where $\lambda \in [0,1]$.

Definition 9. A fuzzy set $\widetilde{A}$ of the universe of discourse X is normal if

$$\max \mu_{\widetilde{A}}(x) = 1.$$

Definition 10. A fuzzy number $\widetilde{N}$ is a fuzzy subset in the universe of discourse X, which is both convex and normal.

Definition 11. The α-cut of the fuzzy set $\widetilde{A}$ of the universe of discourse X is defined as

$$\widetilde{A}_\alpha = \{x \in X \mid \mu_{\widetilde{A}}(x) \geqslant \alpha\},$$

where $\alpha \in [0,1]$.

Definition 12. A triangular fuzzy number $\widetilde{N}$ can be defined as a triplet (l,m,r), and the membership function $\mu_{\widetilde{N}}(x)$ is defined as:

$$\mu_{\widetilde{N}}(x) = \begin{cases} 0, & x < l, \\ (x-l)/(m-l), & l \leqslant x \leqslant m, \\ (r-x)/(r-m) & m \leqslant x \leqslant r, \\ 0, & x > r, \end{cases}$$

where l,m, and r are real numbers and $l \leqslant m \leqslant r$.

Further, in achieving a favorable solution, the group decision-making (GDM) is usually important to any organization. This is because that GDM is the process of arriving at a consensus based upon the reaction of multiple individuals, whereby an acceptable judgment may be obtained (Cheng & Lin, 2002). To deal with the problems of GDM in a fuzzy environment, an effective fuzzy aggregation method is required. Any fuzzy aggregation method always needs to contain a defuzzification method because the results of human judgments with fuzzy linguistic variables are fuzzy numbers. The term defuzzification refers to the selection of a specific crisp element based on the output fuzzy set, which may convert fuzzy numbers into crisp scores (Opricovic & Tzeng, 2003).

There are several useful defuzzification methods that may be divided into two classes by considering either the vertical or the horizontal representation of possibility distribution (Oussalah, 2002). However, a good defuzzification method needs to consider that a fuzzy number is characterized by its shape, spread, height, and relative location on the x-axis (Opricovic & Tzeng, 2003). The most commonly used defuzzification method is the Centroid (Center-of-gravity) method (Yager & Filev, 1994), but this does not distinguish between two fuzzy numbers which have the same crisp value in spite of different shapes. Therefore, we here adopt the CFCS (Converting Fuzzy data into Crisp Scores) defuzzification method for our fuzzy aggregation procedure. This is because the CFCS method can give a better crisp value than the Centroid method.

The CFCS method proposed by Opricovic and Tzeng (2003) is based on the procedure of determining the left and right scores by fuzzy min and fuzzy max, and the total score is determined as a weighted average according to the membership functions. Let $\tilde{z}_{ij}^k = (l_{ij}^k, m_{ij}^k, r_{ij}^k)$ indicate the fuzzy assessments of evaluator k $(k = 1, 2, \ldots, p)$ about the degree to which the criterion i affects the criterion j. The CFCS method includes five-step algorithms described as follows:

(1) Normalization:

$$xl_{ij}^k = (l_{ij}^k - \min l_{ij}^k)/\Delta_{\min}^{\max}, \tag{7}$$

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

$$xr_{ij}^k = (r_{ij}^k - \min l_{ij}^k)/\Delta_{\min}^{\max}, \tag{9}$$

where $\Delta_{\min}^{\max} = \max r_{ij}^k - \min l_{ij}^k$.

(2) Compute left (ls) and right (rs) normalized value:

$$x\mathrm{ls}_{ij}^k = xm_{ij}^k/(1 + xm_{ij}^k - xl_{ij}^k), \tag{10}$$

$$x\mathrm{rs}_{ij}^k = xr_{ij}^k/(1 + xr_{ij}^k - xm_{ij}^k). \tag{11}$$

(3) Compute total normalized crisp value:

$$x_{ij}^k = [x\mathrm{ls}_{ij}^k(1 - x\mathrm{ls}_{ij}^k) + x\mathrm{rs}_{ij}^k x\mathrm{rs}_{ij}^k]/[1 - x\mathrm{ls}_{ij}^k + x\mathrm{rs}_{ij}^k]. \tag{12}$$

(4) Compute crisp values:

$$z_{ij}^k = \min l_{ij}^k + x_{ij}^k \Delta_{\min}^{\max}. \tag{13}$$

(5) Integrate crisp values:

$$z_{ij} = \frac{1}{p}(z_{ij}^1 + z_{ij}^2 + \cdots + z_{ij}^p). \tag{14}$$

3.3. The procedure of fuzzy DEMATEL method

To further the practicality of the DEMATEL method for group decision making in a fuzzy environment, the analytical procedure of our proposed method is explained as follows:

Step 1: Identifying the decision goal and forming a committee. Decision-making is the process of defining the decision goals, gathering relevant information, generating the broadest possible range of alternatives, evaluating the alternatives for advantages and disadvantages, selecting the optimal alternative, and monitoring the results to ensure that the decision goals are achieved (Hess & Siciliano, 1996; Opricovic & Tzeng, 2004). Thus, the first step is to identify the decision goal. Also, it is necessary to form a committee for gathering group knowledge for problem-solving.

Step 2: Developing evaluation factors and designing the fuzzy linguistic scale. In this step, it is necessary to establish sets of significant factors for evaluation. However, evaluation factors have the nature of causal relationships and are usually comprised of many complicated aspects. To gain a structural model dividing involved factors into cause group and effect group, the DEMATEL method must be used here. For dealing with the ambiguities of human assessments, the linguistic variable "influence" is used with five linguistic terms (Li, 1999) as {Very high, High, Low, Very low, No} that are expressed in positive triangular fuzzy numbers (l_{ij}, m_{ij}, r_{ij}) as shown in Table 1.

Step 3: Acquiring and aggregating the assessments of decision makers. To measure the relationship between evaluation factors $C = \{C_i | i = 1, 2, \ldots, n\}$, it is usually necessary to ask a group of experts to make assessments in terms of influences and directions between factors. Then, using the CFCS method, those fuzzy assessments are defuzzified and aggregated as a crisp value which is the z_{ij}. Hence, the initial direct-relation matrix $Z = [z_{ij}]_{n \times n}$ can be obtained by formulas (7)–(14).

Step 4: Establishing and analyzing the structural model. On the base of the initial direct-relation matrix Z, the normalized direct-relation matrix X can be obtained through formulas (1). Then, the total-relation matrix T can be acquired by using formula (3). According to Definitions 5 and 6, a causal diagram can be acquired through formulas (4)–(6). The causal diagram is constructed with the horizontal axis $(D + R)$ named "Prominence" and the vertical axis $(D - R)$ named "Relation". The horizontal axis "Prominence" shows how much importance the factor has, whereas the vertical axis "Relation" may divide factors into cause group and effect group. Generally, when the $(D - R)$ axis is plus, the factor belongs to the cause

Table 1
The fuzzy linguistic scale

Linguistic terms	Triangular fuzzy numbers
Very high influence (VH)	(0.75, 1.0, 1.0)
High influence (H)	(0.5, 0.75, 1.0)
Low influence (L)	(0.25, 0.5, 0.75)
Very low influence (VL)	(0, 0.25, 0.5)
No influence (No)	(0, 0, 0.25)

group. Otherwise, the factor belongs to the effect group if the $(D - R)$ axis is minus. Hence, causal diagrams can visualize the complicated causal relationships of factors into a visible structural model, providing valuable insight for problem-solving. Further, with the help of a causal diagram, we may make proper decisions by recognizing the difference between cause and effect factors.

4. Empirical study and discussions

Facing global competition, all companies need to enrich the required competencies for their global managers. In this section, an empirical study shows how a high-tech company applied our proposed method to segment the eight IQs for promoting competency development successfully.

4.1. Problem descriptions

The case Company P is a Taiwan firm with more than USD 860 million turnover and over 1428 employees. The company is one of the world's leading manufacturers in the RAID (Redundant Array of Inexpensive Disks) market, offering high-capacity storage products and data protection storage solutions. Due to the worldwide challenge posed by the trend toward shorter product cycles and lower costs for consumer electronics, Company P requires performing with shorter lead-time, higher quality, competitive prices, and improved customer service in a global context.

Under the pressure of the fierce global competition, Company P wished to develop the competencies of their global managers by using the eight different IQs. However, those eight IQs are difficult to execute at the same time, but are better suited to promote in a stepwise manner. Also, Company P encountered the problems concerning how to segment those eight IQs into meaningful portions and how to integrate the fuzzy judgments of GDM. In order to acquire sensible segments, Company P therefore adopted our proposal and set up a competency development committee consisting of the General Manager, and several managers representing the marketing, financial, production, human resource, and information technology departments. The following shows how Company P utilized our proposed fuzzy DEMATEL method to evaluate and segment the eight IQs for better implementing the competency development of their global managers.

4.2. Applications of proposed method

The committee followed our proposed method with the four-step procedure. First, they defined the decision goals for segmenting the eight IQs into portions in order to promote the competency development of their global managers step by step. In step 2, the committee adopted the eight IQs as evaluation factors, including: cognitive IQ (C_1); emotional IQ (C_2); political IQ (C_3); cultural/social IQ (C_4); organizational IQ (C_5); network IQ (C_6); innovative IQ (C_7); and intuitive IQ (C_8). Also, they decided to use a fuzzy linguistic scale (Table 1) for making assessments. In step 3, once the relationships between those factors were measured by the committee through the use of the fuzzy linguistic scale, the data from each individual assessment could be obtained. For example, the assessment data of the General Manager are shown in Table 2. Then, using the CFCS method to aggregate these assessment data, the initial direct-relation matrix (Table 3) was produced.

In step 4, based on the initial direct-relation matrix, the normalized direct-relation matrix (Table 4) was obtained by formula (1) and (2). Next, the total-relation matrix (Table 5) was acquired by using formula (3). Then, using formulas (4)–(6), the causal diagram (Fig. 1) could be acquired by mapping a dataset of $(D + R, D - R)$. Looking at this causal diagram, it is clear that evaluation factors were visually divided into the cause group, including C_1, C_2, C_7 and C_8 while the effect group was composed of such factors as C_3, C_4, C_5 and C_6.

Table 2
The assessment data of the General Manager

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	No	H	VL	L	H	H	L	VL
C_2	L	No	VL	H	VL	VL	L	L
C_3	VL	VL	No	H	L	L	VL	No
C_4	VL	VH	L	No	L	L	L	H
C_5	VL	VL	H	L	No	H	L	VL
C_6	L	VL	L	VL	H	No	VL	VL
C_7	H	VL	L	VL	VH	H	No	H
C_8	L	H	No	H	VL	VL	L	No

Table 3
The initial direct-relation matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.000	0.609	0.533	0.567	0.673	0.810	0.641	0.533
C_2	0.533	0.000	0.367	0.705	0.400	0.400	0.705	0.667
C_3	0.567	0.333	0.000	0.333	0.533	0.673	0.198	0.233
C_4	0.600	0.641	0.263	0.000	0.300	0.327	0.633	0.500
C_5	0.500	0.400	0.770	0.400	0.000	0.633	0.433	0.333
C_6	0.770	0.333	0.600	0.400	0.600	0.000	0.400	0.367
C_7	0.705	0.467	0.391	0.333	0.802	0.633	0.000	0.673
C_8	0.467	0.770	0.333	0.600	0.267	0.400	0.633	0.000

Table 4
The normalized direct-relation matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.000	0.090	0.079	0.084	0.100	0.120	0.095	0.079
C_2	0.079	0.000	0.054	0.104	0.059	0.059	0.104	0.099
C_3	0.084	0.049	0.000	0.049	0.079	0.100	0.029	0.035
C_4	0.089	0.095	0.039	0.000	0.044	0.048	0.094	0.074
C_5	0.074	0.059	0.114	0.059	0.000	0.094	0.064	0.049
C_6	0.114	0.049	0.089	0.059	0.089	0.000	0.059	0.054
C_7	0.104	0.069	0.058	0.049	0.119	0.094	0.000	0.100
C_8	0.069	0.114	0.049	0.089	0.040	0.059	0.094	0.000

Table 5
The total-relation matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	0.111	0.177	0.163	0.167	0.189	0.213	0.185	0.163
C_2	0.170	0.086	0.127	0.175	0.141	0.147	0.184	0.171
C_3	0.153	0.110	0.063	0.108	0.140	0.164	0.095	0.093
C_4	0.167	0.163	0.105	0.072	0.119	0.127	0.165	0.142
C_5	0.158	0.130	0.176	0.127	0.079	0.171	0.136	0.117
C_6	0.193	0.124	0.156	0.128	0.162	0.087	0.134	0.123
C_7	0.197	0.153	0.140	0.132	0.199	0.184	0.091	0.174
C_8	0.155	0.183	0.117	0.157	0.117	0.139	0.169	0.076

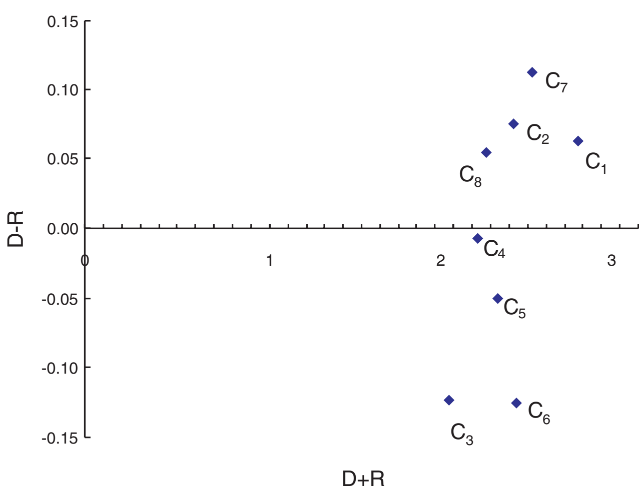

Fig. 1. The causal diagram.

4.3. Discussions

In this empirical study, the case Company planned to enhance the competencies of their global managers through the eight IQs. According to the evaluation results, we can derive several implications about business management as follows:

Firstly, valuable cues can be obtained for making profound decisions from the causal diagram (Fig. 1). For example, if we wanted to obtain high performances in terms of the effect group factors, it would be necessary to control and pay a great deal of attention to the cause group factors beforehand. This is because the cause group factors imply the meaning of the influencing factors, whereas the effect group factors denote the meaning of the influenced factors (Fontela & Gabus, 1976). In other words, the cause group factors are difficult to move, while the effect group factors are easily moved (Hori & Shimizu, 1999). Hence, among these eight IQs, the cognitive IQ (C_1) is the most important factor because it has the highest intensity of relation to other factors; moreover, the innovative IQ (C_7) is the most influencing factor, but it is quite difficult to move.

Secondly, training and development (T&D) attempt to increase employees' competencies in order to make them work better with high performances. However, training is mainly used to provide required knowledge and skills to employees for improving performance, whereas development focuses on ways to expand employees' mental ability and brain power. This implies that the effect group IQs (political IQ, cultural/social IQ, organizational IQ, and network IQ) can be improved by training, while the cause group IQs (cognitive IQ, emotional IQ, innovative IQ, and intuitive IQ) need more efforts of development.

Thirdly, a competency model usually contains a list of required competencies, in which some are easier to be changed through training but others are not so. Referring to the five types of competency characteristics (Spencer & Spencer, 1993), knowledge and skills are relatively easy to develop through training, while motive, trait and self-concept are more difficult to assess and develop. In this sense, the cause group IQs is difficult to be changed, so that it can be used as the critical criteria for recruiting the right global managers.

5. Conclusions

In the current borderless economy, companies have the continual need to be globally efficient and competitive by integrating activities and resources across national borders. To this end, companies need to pay careful attention to select the right global manager and to expand their managerial competencies through using competency models. However, a competency model often contains a list of numerous competencies. It is difficult for anyone to master a broad set of competencies simultaneously. There arises an important issue in terms of segmenting a set of competencies into some meaningful portions in order to effectively facilitate competency development. Additionally, to handle this issue, it is also necessary to solve the matter of integrating group decision-making in fuzzy environments.

Hence, we proposed the fuzzy DEMATEL method to achieve segmentation of required competencies for better implementing the competency development of global managers. Our proposed method successfully extends the DEMATEL method by applying both linguistic variables and a fuzzy aggregation method, so that it can effectively deal with vague and imprecise judgments. In particular, this proposed method can also successfully divide a set of complex factors into a cause group and an effect group, and produce a visible causal diagram. Through the causal diagram, the complexity of a problem is easier to capture, whereby profound decisions can be made.

As concerns our empirical study, the proposed fuzzy DEMATEL method worked smoothly in tackling the issue of segmenting the eight IQs into meaningful portions. According to the analysis results, these IQs (the cognitive IQ, emotional IQ, innovative IQ, and intuitive IQ) are difficult to be changed through training but must be expanded by development. This implies that it is an effective way to expand global managers' competencies by these four IQs with high priority. Further, these IQs can be regarded as the critical criteria in recruiting the right global managers.

Our proposed fuzzy DEMATEL method is comprehensive and applicable to all companies facing problems that require group decision-making in a fuzzy environment to segment complex factors. As for future research, one possible direction may be to research a more satisfying fuzzy aggregation method.

References

Al-Najjar, B., & Alsyouf, I. (2003). Selecting the most efficient maintenance approach using fuzzy multiple criteria decision making. *International Journal of Production Economics, 84*(1), 85–100.

Asan, U., Erhan Bozdag, C., & Polat, S. (2004). A fuzzy approach to qualitative cross impact analysis. *Omega, International Journal of Management Science, 32*(6), 443–458.

Athey, T. R., & Orth, M. S. (1999). Emerging competency methods for the future. *Human Resource Management, 38*(3), 215–226.

Bellman, R. E., & Zadeh, L. A. (1970). Decision-making in a fuzzy environment. *Management Science, 17*(4), 141–164.

Boyatzis, R. E. (1982). *The competent manager: A model for effective performance*. New York: John Wiley & Sons.

Boyatzis, R. E., Goleman, D., & Rhee, K. (1999). Clustering competence in emotional intelligence: Insights from the Emotional Competence Inventory (ECI). In R. Bar-on & J. D. Parker (Eds.), *Handbook of emotional intelligence*. San Francisco: Jossey-Bass.

Chang, Y. H., Yeh, C. H., & Cheng, J. H. (1998). Decision support for bus operations under uncertainty: A fuzzy expert system approach. *Omega, International Journal of Management Science, 26*(3), 367–380.

Chen, L. H., & Chiou, T. W. (1999). A fuzzy credit-rating approach for commercial loans: A Taiwan case. *Omega, International Journal of Management Science, 27*(4), 407–419.

Chen, S. J., Hwang, C. L., & Hwang, F. P. (1992). *Fuzzy multiple attribute decision making methods and applications*. New York: Springer.

Cheng, C. H., & Lin, Y. (2002). Evaluating the best main battle tank using fuzzy decision theory with linguistic criteria evaluation. *European Journal of Operational Research, 142*(1), 174–186.

Dive, B. (2004). *Education management*. Auckland: New Zealand Management.

Delgado, M., Verdegay, J. L., & Vila, M. A. (1992). Linguistic decision-making models. *International Journal of Intelligent System, 7*(3), 479–492.

Fontela, E., & Gabus, A. (1976). *The DEMATEL observer, DEMATEL 1976 report*. Switzerland Geneva: Battelle Geneva Research Center.

Gabus, A., & Fontela, E. (1972). *World problems, an invitation to further thought within the framework of DEMATEL*. Switzerland, Geneva: Battelle Geneva Research Centre.

Gabus, A., & Fontela, E. (1973). *Perceptions of the world problematique: Communication procedure, communicating with those bearing collective responsibility (DEMATEL report no. 1)*. Switzerland Geneva: Battelle Geneva Research Centre.

Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. New York: Basic Books.

Goleman, D. (1998). *Working with emotional intelligence*. New York: Bantam.

Harvey, M. G., & Richey, R. G. (2001). Global supply chain management: The selection of globally competent managers. *Journal of International Management, 7*(4), 105–128.

Harvey, M., Novicevic, M. M., & Kiessling, T. (2002). Development of multiple IQ maps for use in the selection of inpatriate managers: a practical theory. *International Journal of Intercultural Relations, 26*(4), 493–524.

Hellriegel, D., Jackson, S. E., & Slocum, J. W. (2002). *Management: A competency-based approach*. South-Western: Thomson Learning.

Hess, P., & Siciliano, J. (1996). *Management: Responsibility for performance*. New York: McGraw-Hill.

Hori, S., & Shimizu, Y. (1999). Designing methods of human interface for supervisory control systems. *Control Engineering Practice, 7*(11), 1413–1419.

JPC-SED (2002). The fifth survey on changes in the Japanese-style personnel system. Tokyo: Japan Productivity Center for Socio-Economic Development.

Kamaike, M. (2001). Design elements in the passenger car development: The classification and the influence analysis in case of recreational vehicle. *Japanese Society for the Science of Design, 48*(1), 29–38.

Kelner, S. P. (2001). A few thoughts on executive competency convergence. *Center for Quality of Management Journal, 10*(1), 67–72.

Li, R. J. (1999). Fuzzy method in group decision making. *Computers and Mathematics with Applications, 38*(1), 91–101.

Malaviya, A., & Peters, L. (1997). Fuzzy feature description of handwriting patterns. *Pattern Recognition, 30*(10), 1591–1604.

Mansfield, R. S. (1996). Building competency models: Approaches for HR professionals. *Human Resource Management, 35*(1), 7–18.

McClelland, D. C. (1973). Testing for competence rather than for intelligence. *American Psychologist, 28*(1), 1–24.

McKenna, S. (1998). Cross-cultural attitudes towards leadership dimensions. *Leadership and Organization Development Journal, 19*(2), 106–119.

Mirable, R. (1997). Everything you wanted to know about competency modeling. *Training and Development, 51*(8), 73–77.

Opricovic, S., & Tzeng, G. H. (2003). Defuzzification within a multicriteria decision model, International Journal of Uncertainty. *Fuzziness and Knowledge-Based Systems, 11*(5), 635–652.

Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. *European Journal of Operational Research, 156*(2), 445–455.

Oussalah, M. (2002). On the compatibility between defuzzification and fuzzy arithmetic operations. *Fuzzy Sets and Systems, 128*(2), 247–260.

Quinn, R. E., Faerman, S. R., Thompson, M. P., & McGrath, M. (1996). *Becoming a master manager: A competency framework*. New York: John Wiley & Sons.

Rodriguez, D., Patel, R., Bright, A., Gregory, D., & Gowing, M. K. (2002). Developing competency models to promote integrated human resource. *Human Resource Management, 41*(3), 309–324.

Rosen, R., & Digh, P. (2001). Developing globally literate leaders. *Training and Development, 55*(5), 70–81.

Schoonover, S. C., Schoonover, H., Nemerov, D., & Ehly, C. (2000). *Competency-based HR applications: Results of a comprehensive survey*. Reports of the Arthur Andersen, Schoonover, SHRM, Virginia: Alexandria.

Sheridan, A. (1997). Think globally – act locally! Competences for global management. *Career Development International, 2*(6), 308–309.

Sinkovics, R. R., Bell, J., & Deans, K. R. (2004). Using information communication technology to develop international entrepreneurship competencies. *Journal of International Entrepreneurship, 2*(1–2), 125–137.

Sinnott, G. C., Madison, G. H., & Pataki, G. E. (2002). *Competencies: Report of the competencies workgroup, workforce and succession planning work groups*. New York: New York State Governor's Office of Employee Relations and the Department of Civil Service.

Spencer, L. M., & Spencer, S. M. (1993). *Competence at work: Model for superior performance*. Inc, New York: John Wiley & Sons.

Sternberg, R. J. (1985). *Beyond IQ: A triarchic theory of human intelligence*. New York: Cambridge University Press.

Sternberg, R. J. (1997). Managerial intelligence: Why IQ isn't enough. *Journal of Management, 23*(3), 475–493.

Von Altrock, C. (1996). *Fuzzy logic and neurofuzzy applications in business and finance*. New Jersey: Prentice-Hall.

Wu, W. W., Lee, Y. T., & Tzeng, G. H. (2005). Simplifying the manager competency model by using the rough set approach. In Dominik Slezak, JingTao Yao, James F. Peters, Wojciech Ziarko, & Xiaohua Hu (Eds.), *Rough sets, fuzzy sets, data mining, and granular computing. LNAI 3642* (Part II) (pp. 484–495).

Yager, R. R., & Filev, D. P. (1994). *Essentials of fuzzy modeling and control*. New York: John Wiley & Sons.

Yamazaki, M., Ishibe, K., Yamashita, S., Miyamoto, I., Kurihara, M., & Shindo, H. (1997). An analysis of obstructive factors to welfare service using DEMATEL method. Reports of the Faculty of Engineering. *Yamanashi University, 48*(1), 25–30.

Yuzawa, A. (2002). A state and subjects of TMO conception for city core vitalization countermeasure: A case study of Maebashi TMO Conception. *Bulletin of Maebashi Institute of Technology, 5*(1), 61–67.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(2), 338–353.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Information Science, 8*(2), 199–249, 301–357(II).