Evaluating the Knowledge Management Capability of Organizations through a Fuzzy Linguistic Approach

Jian Ma
Department of Information Systems, City University of Hong Kong, Kowloon, Hong Kong, China
isjian@cityu.edu.hk

Yong-Hong Sun
School of Business Administration, Northeastern University, Shenyang 110004, China
yhsun@mail.neu.edu.cn

Zhi-Ping Fan
School of Business Administration, Northeastern University, Shenyang 110004, China
zpfan@mail.neu.edu.cn

Abstract

This paper presents a group evaluation structure model for evaluating the knowledge management capability (KMC) of an organization. An algorithm is also proposed to determine the degrees of KMC of an organization using a fuzzy linguistic approach. With the results of the degree of KMC, an organization can decide when and where to improve its KMC. A practical example is used to illustrate the application of the proposed method. The results of KMC obtained through the proposed method are objective and unbiased due to the following two reasons. Firstly, the results are generated by a group of evaluators. Secondly, the fuzzy linguistic approach used in this paper has the advantage to reduce information distortion and losing over other fuzzy linguistic approaches.

Keywords: Knowledge management (KM), Knowledge management capability (KMC), Linguistic assessment information, 2-tuple

1. Introduction

Knowledge management (KM) has been described for its possible role in creating sustained competitive advantages for organizations [1, 2, 3, 4, 5]. The contributions of KM to competitive advantage include: improved ability to innovate, improved coordination of efforts, and rapid commercialization of new products. Other contributions include: the ability to anticipate surprise, responsiveness to market change, and reduced redundancy of information/knowledge. Many organizations are launching extensive knowledge management efforts. Unfortunately, many knowledge management projects are, in reality, information projects. When these projects yield some consolidation of data but little innovation in products and services, the concept of knowledge management is cast in doubt [6]. The main reason for this problem is that organizations may not identify and assess the preconditions that are necessary for the KM effort to flourish. Therefore, organizations can’t understand the success and failure of knowledge management within organizations. These preconditions are described broadly as “capability” or “resources” within the organizational behavior literature [7, 8, 9].

There has been some research dealing with KMC. Desouza [10] argues that the ideal organization with well-matured KMC can ensure the identification, distribution, protection, application, and destruction of knowledge. Therefore, KMC is the key to pre-empting an organizational crisis. Lubit [11] argues that tacit knowledge and superior KMC are now the keys to sustainable competitive advantage in many industries. All these theoretical studies develop the concepts and improve the understanding of KMC. At the same time, there also are several empirical studies that enrich the research outcomes of this field. Collinson [13]
emphasize the significance of contextual factors for transferring some KM practices by case study. Bresnen et al. [14] examined the significance of social factors in enhancing KMC in project environments by case study. Liu et al. [12] examined the association between KMC and competitiveness by empirical analysis. The result reveals that KMC has a tremendous effect on organizational competitiveness. KMC is considered more than a catch-all for information and knowledge. It is a tool for maintaining information and knowledge that will help us to work more efficiently [12]. Gold et al. [6] and Chuang [4] presented and validated the framework for analyzing KMC using different dimensions. The research work by Gold et al. and Chuang makes the KMC theory more easily operational. Thus, some efforts have been made to emphasize the significance of KMC, and analyze and explore the dimensions of KMC. However, the importance of capability dimensions and the subjective evaluation of KMC have seldom been addressed.

Indeed, there are many kinds of methods that can be used to evaluate the degree of KMC. For example, scoring tool may be the simplest method to evaluate the degree of KMC. However, usually, most evaluators cannot give exact numerical values to express their opinions based on human perception: more realistic measurement uses linguistic assessments instead of numerical values [15, 16, 17, 18, 19]. In fact, dimensions can be measured as linguistic labels (terms) such as very high, high, middle, low, and very low [39]. After Zadeh [20] introduced fuzzy set theory to deal with vague problems, linguistic labels have been used within the framework of fuzzy set theory [21] to handle the ambiguity in evaluating data and the vagueness of linguistic expression[39].

Therefore, the purpose of this study was to establish a group evaluation structure model of KMC for organizations. An algorithm is proposed to assess the degree of KMC in a fuzzy environment using a fuzzy linguistic approach. Section 2 presents a fuzzy linguistic approach to evaluating KMC of organizations. Section 3 proposes a hierarchical structure model of KMC for organizations. Assume that a group of n experts (E₁, E₂, … Eₙ) are responsible for assessing the degree of KMC for management. The proposed method aggregates each parameter assessed by an individual, and aggregates the results to determine the final degree of KMC. Section 4 considers this algorithm. Section 5 illustrates the practical application of proposed method in the National Natural Science Foundation of China (NSFC).

2. Fuzzy Linguistic Approach

2.1 Linguistic Assessments

The fuzzy linguistic approaches assess linguistic variables using words or sentences of a natural language [21]. This approach is appropriate for some problems in which information may be qualitative, or quantitative information may not be stated precisely, since either it is unavailable or the cost of its determination is excessive, such that an ‘approximate value’ suffices [17, 39].

Usually, most experts will provide linguistic assessments rather than exact numerical values to express their opinions on KMC. As demonstrated in Gold’s study, both infrastructure and process capability predict performance. Therefore, manager’s who only optimize one aspect of the knowledge management effort may suboptimize the entire effort [6]. So, when applying a fuzzy linguistic approach to measuring KMC, both the two aspects of KMC are considered. Furthermore, the importance of dimensions in two aspects, based on the KM strategy is considered. For example, when determining infrastructure side of KMC,
performance should be measured according to its dimensions and the importance of each dimension should also be determined.

As mentioned above, the rating of performance and grade of importance should be rated for each item. Therefore, both were scored on a nine-rank scale, as shown in Table 1. Let \( S = \{ S_0, S_1, \ldots, S_8 \} \) be a finite and totally ordered term set and with an odd cardinality, where the middle label, \( S_4 \), represents ‘average’, and the remaining terms are placed symmetrically around \( S_4 \), and exhibit the following properties [22, 39].

1. The set is ordered: \( S_i \geq S_j \) if \( i \geq j \), where "\( \geq \)" denotes greater than.
2. There is a negation operator: \( \text{Neg}(S_j) = S_j \) such that \( j = 8 - i \), where 9 is the cardinality of the set \( S \).
3. Maximization operator: \( \text{MAX}(S_i, S_j) = S_i \) if \( S_i \geq S_j \).
4. Minimization operator: \( \text{MIN}(S_i, S_j) = S_j \) if \( S_i \geq S_j \).

### Table 1

<table>
<thead>
<tr>
<th>Nine ranks of rating of performance</th>
<th>Nine ranks of grade of importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_0 = \text{DL: definitely low} )</td>
<td>( S_0 = \text{DL: definitely low} )</td>
</tr>
<tr>
<td>( S_1 = \text{VL: very low} )</td>
<td>( S_1 = \text{VL: very low} )</td>
</tr>
<tr>
<td>( S_2 = \text{L: low} )</td>
<td>( S_2 = \text{L: low} )</td>
</tr>
<tr>
<td>( S_3 = \text{ML: more or less low} )</td>
<td>( S_3 = \text{ML: more or less low} )</td>
</tr>
<tr>
<td>( S_4 = \text{M: middle} )</td>
<td>( S_4 = \text{M: middle} )</td>
</tr>
<tr>
<td>( S_5 = \text{MH: more or less high} )</td>
<td>( S_5 = \text{MH: more or less high} )</td>
</tr>
<tr>
<td>( S_6 = \text{H: high} )</td>
<td>( S_6 = \text{H: high} )</td>
</tr>
<tr>
<td>( S_7 = \text{VH: very high} )</td>
<td>( S_7 = \text{VH: very high} )</td>
</tr>
<tr>
<td>( S_8 = \text{DH: definitely high} )</td>
<td>( S_8 = \text{DH: definitely high} )</td>
</tr>
</tbody>
</table>

The nine linguistic labels in \( S = \{ S_0, S_1, \ldots, S_8 \} \) were specified. This paper considers a situation in which experts can perfectly distinguish among the set of labels under a similar conception, and can use linguistic labels to express their opinions [39].

### 2.2 2-tuple Linguistic Representation Model

The methods for dealing with linguistic information can be classified into three categories [23]. The first one is based on the Extension Principle [24, 25, 17, 26, 27, 28, 29, 30, 31]. It makes operations on the fuzzy numbers that support the semantics of the linguistic terms. The second one is the symbolic method [32, 22, 33]. It makes computations on the indexes of the linguistic terms. The third one is based on 2-tuple fuzzy linguistic representation model [23, 34]. In the former two methods, the results usually do not exactly match any of the initial linguistic terms, and then an approximation process must be developed to express the result in the initial expression domain. This produces the consequent loss of information and hence the lack of precision [25]. The third method overcomes the above limitation. The model represents the linguistic information with a pair of values, which is called 2-tuple, composed by a linguistic term and a number. The main advantage of this representation is to be continuous in its domain; therefore, it can express any counting of information in the universe of the discourse. Thus, the third method is more convenient and precise when dealing with fuzzy linguistic information. Because of the length constraint, the comparative analyses among these three kinds of methods will not be explained here. The detailed comparative results are illustrated in Francisco Herrera’s research [23].
2-tuple linguistic representation model, presented in [23, 34, 36, 37, 38], is based on the concept of Symbolic Translation. It is used for representing the linguistic information by means of 2-tuple \((s_i, \alpha_i)\), where \(s_i\) is labels from predefined linguistic term set \(S\), and \(\alpha_i\) is the difference value between calculated linguistic term set and most approximate label in initial linguistic term set. Generally, \(\alpha_i (\alpha_i \in [-0.5, 0.5])\) represents the symbolic translation.

Let \(s_i \in S\) be a linguistic label. Then the function \(\theta\) used to obtain the corresponding 2-tuple linguistic information of \(s_i\) is defined as:

\[
\theta : S \rightarrow S \times [-0.5, 0.5),
\]

\[
\theta(s_i) = (s_i, 0), \quad s_i \in S.
\]  

(2.1)

Let \(S = \{s_0, s_1, \cdots, s_T\}\) be a linguistic term set, \(\beta_i \in [0, T]\) is a number value representing the aggregation result of linguistic symbolic. Then the function \(\Delta\) used to obtain the 2-tuple linguistic information equivalent to \(\beta_i\) is defined as:

\[
\Delta : [0, T] \rightarrow S \times [-0.5, 0.5),
\]

\[
\Delta(\beta) = (s_i, \alpha_i), \quad \text{with } \begin{cases} s_i = \text{Round}(\beta_i) \\ \alpha_i = \beta_i - i, \quad \alpha_i \in [-0.5, 0.5) \end{cases}
\]  

(2.2)

where “Round” is the usual round operation. \(s_i\) has the closest index label to \(\beta\) and \(\alpha_i\) is the value of the symbolic translation. If \(S\) is a linguistic term set, \(S = \{s_0, s_1, \cdots, s_T\}\), \((s_i, \alpha_i)\) is 2-tuple linguistic information, then there exists a function \(\Delta^{-1}\), which is able to transfer 2-tuple linguistic information into it equivalent numerical value \(\beta_i \in [0, T]\). The function \(\Delta^{-1}\) is defined as:

\[
\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, T],
\]

\[
\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta_i.
\]  

(2.3)

If \((s_i, \alpha_i)\) and \((s_j, \alpha_j)\) are two linguistic 2-tuples, they should have the following properties:

1. The set is ordered:
   - if \(i \geq j\), then \((s_i, \alpha_i) > (s_j, \alpha_j)\), where “>” denotes “greater than”;
   - if \(i = j\), then
     - if \(\alpha_i > \alpha_j\), then \((s_i, \alpha_i) > (s_j, \alpha_j)\);
     - if \(\alpha_i = \alpha_j\), then \((s_i, \alpha_i) = (s_j, \alpha_j)\), where “=” denotes “equal to”;
     - if \(\alpha_i < \alpha_j\), then \((s_i, \alpha_i) < (s_j, \alpha_j)\), where “<” denotes “less than”.

2. There exists a negation operator: \(\text{Neg}((s_i, \alpha_i)) = \Delta(T - (\Delta^{-1}(s_i, \alpha_i)))\), such that, where \(T + 1\) is the cardinality of the set \(L\) (or \(S\)).

3. Maximization operator: \(\text{MAX}\{s_i, \alpha_i, s_j, \alpha_j\} = (s_i, \alpha_i)\) if \((s_i, \alpha_i) \geq (s_j, \alpha_j)\).

4. Minimization operator: \(\text{MIN}\{s_i, \alpha_i, s_j, \alpha_j\} = (s_j, \alpha_j)\) if \((s_j, \alpha_j) \geq (s_i, \alpha_i)\).

Let \((b_1, \alpha_1), (b_2, \alpha_2), \cdots, (b_m, \alpha_m)\) be a group of linguistic 2-tuples to be aggregated, then 2-tuple arithmetic mean operator \(\overline{B^\epsilon}\) is defined as:

\[
\overline{B^\epsilon} = (\overline{b}, \overline{\alpha}) = \Delta \left( \sum_{i=1}^{m} \frac{1}{m} \Delta^{-1}(b_i, \alpha_i) \right), \quad \overline{b} \in S; \overline{\alpha} \in [-0.5, 0.5).
\]  

(2.4)
Let \((b_1, \alpha_1), (b_2, \alpha_2), \ldots, (b_m, \alpha_m)\) be a serial of linguistic 2-tuples to be aggregated, \(R = ((r_1, \alpha'_1), (r_2, \alpha'_2), \ldots, (r_m, \alpha'_m))^T\) be its equivalent 2-tuple weighted vector, then 2-tuple weighted average operator \(\hat{B}^*\) is defined as:

\[
\hat{B}^* = (\hat{b}, \hat{\alpha}) = \Delta \left( \frac{\sum\limits_{i=1}^{m} [\Delta^{-1}(r_i, \alpha'_i) \times \Delta^{-1}(b_i, \alpha_i)]}{\sum\limits_{i=1}^{m} \Delta^{-1}(r_i, \alpha'_i)} \right), \hat{b} \in S; \hat{\alpha} \in [-0.5, 0.5).
\] (2.5)

3. Hierarchical Structure Model of KMC

A systematic approach is proposed to assess the degree of KMC, using a fuzzy linguistic approach and hierarchical structure analysis. This method is suited to aggregate group opinions in a fuzzy environment.

The contents of KMC presented by Gold et al. [6] and Chuang [4] were expressed two aspects and seven dimensions. One aspect is infrastructure capability, including dimensions such as technology, structure and culture. The other aspect is process capability, including dimensions such as acquisition, conversion, application and protection. Gold et al.’s argues that knowledge capabilities are additive in nature according to the empirical research. Infrastructure capability is a sum of technological, structural and cultural capability. Likewise, process capability is an additive effect of acquisition, conversion, application, and protection capability. So, KMC can be determined by its dimensions. For convenience, the infrastructure capability was represented as \(X\). Its dimensions were represented as \(X_1, X_2\) and \(X_3\) accordingly. Likewise, the process capability was represented as \(Y\). Its dimensions were represented as \(Y_1, Y_2, Y_3\) and \(Y_4\). The hierarchical structure model of KMC is showed as Fig. 1. The grades of importance of these dimensions depend on the industry to which an organization belongs and the strategy that the organization implements. Furthermore, in order to facilitate experts to provide precise judgments on KMC, the contents of KMC were described in detail as shown in Tables 2 and 3.
Fig. 1. Hierarchical structure model of KMC (Source: Literature [6, 4])

Table 2
The contents of Infrastructure Capability (Source: Literature [6, 4])

<table>
<thead>
<tr>
<th>Technology</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>business intelligence</td>
<td>Generate knowledge regarding a firm's competition and broader economic environment.</td>
</tr>
<tr>
<td>Collaboration</td>
<td>Eliminate the structural and geographical impediments, and allow individuals within the organization to collaborate.</td>
</tr>
<tr>
<td>knowledge discovery</td>
<td>Allow a firm to find new knowledge that is either internal or external to the firm.</td>
</tr>
<tr>
<td>knowledge mapping</td>
<td>Track source of knowledge, and create catalogs of internal organizational knowledge.</td>
</tr>
<tr>
<td>opportunity generation</td>
<td>Track knowledge about a firm's customers, partners, employees, or suppliers.</td>
</tr>
<tr>
<td>Security</td>
<td>Ensure that knowledge is not stolen or used inappropriately.</td>
</tr>
</tbody>
</table>

Table 3
The contents of Process Capability (Source: Literature [6, 4])

<table>
<thead>
<tr>
<th>Acquisition</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seek and acquire entirely new knowledge; Create new knowledge out of existing knowledge</td>
<td></td>
</tr>
</tbody>
</table>
The experts consider the grade of importance and related rating of performance, grading both as $S = \{S_0, S_1, \ldots, S_8\}$. Suppose a group of experts $(E_1, E_2, \ldots, E_n)$ are responsible for assessing the degree of KMC (Suppose the opinions of experts have the equal importance.). The symbol $p_{jm}$ is used to denote the grade of importance of dimension $X_m$ in infrastructure capability; $u_{jm}$ the rating of performance of dimension $X_m$, according to assessment data of expert $E_j$ ($j=1,2,\ldots,n; \quad m=1,2,3$). Likewise, The symbol $q_{jl}$ is used to denote the grade of importance of dimension $Y_l$ in infrastructure capability; $v_{jl}$ the rating of performance of dimension $Y_l$, according to expert $E_j$’s assessing data ($j=1,2,\ldots,n; \quad l=1,2,3,4$). Table 4 represents the above given the data assessed by expert $E_j$ ($j=1,2,\ldots,n$). The data assessed by all $n$ experts are combined to evaluate the final degree of KMC.

A corresponding algorithm is considered as follows:

\[
\{E_1, E_2, \ldots, E_n\} \Rightarrow E \Rightarrow \text{solution}
\]

is based on an aggregated preference relation of the group. Therefore, the following section of this paper proposes the algorithm for evaluating the degree of KMC for management by a group of experts.

### Table 4

The contents of model

<table>
<thead>
<tr>
<th>KMC</th>
<th>$X$ (Infrastructure capability)</th>
<th>$Y$ (Process capability)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capability dimensions</td>
<td>$X_1$</td>
<td>$Y_1$</td>
</tr>
<tr>
<td>Grade of importance</td>
<td>$P(X_1)$</td>
<td>$Q(Y_1)$</td>
</tr>
<tr>
<td>Rating of performance</td>
<td>$U(X_1)$</td>
<td>$V(Y_1)$</td>
</tr>
<tr>
<td></td>
<td>$X_2$</td>
<td>$Y_2$</td>
</tr>
<tr>
<td></td>
<td>$P(X_2)$</td>
<td>$Q(Y_2)$</td>
</tr>
<tr>
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<td>$U(X_2)$</td>
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<td>$X_3$</td>
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<tr>
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<td>$P(X_3)$</td>
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<td></td>
<td>$U(X_3)$</td>
<td>$V(Y_3)$</td>
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<tr>
<td></td>
<td></td>
<td>$Y_4$</td>
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<tr>
<td></td>
<td></td>
<td>$Q(Y_4)$</td>
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<tr>
<td></td>
<td></td>
<td>$V(Y_4)$</td>
</tr>
</tbody>
</table>

### 4. Algorithm

This algorithm aggregates each parameter assessed by an individual, and aggregates the results to produce the final degree of KMC. Firstly, the infrastructure capability is computed. The calculating steps of the method are given below.

**Step 1-1:** Let $u_{jm}$ and $p_{jm}$ be linguistic labels in $S = \{S_0, S_1, \ldots, S_8\}$. Then transform them into 2-tuple linguistic information

Through the transformation function $\theta$ defined above, transform $u_{jm}$ and $p_{jm}$ into $(u_{jm}, 0)$ and $(p_{jm}, 0)$

**Step 1-2:** First stage assessment. According to the operator $B^e$ with equation (2.4), the aggregated parameters obtained from the $n$ experts’ linguistic data can be expressed as follows:
\[(u_m, \alpha_m) = \Delta \left( \sum_{j=1}^{n} \frac{1}{n} \Delta^{-1}(u_{jm}, \alpha_{jm}) \right) \text{ for } m=1, 2, 3, u_m \in S, \text{ and } \alpha_m \in [-0.5,0.5), \tag{4.1} \]

\[(p_m, \alpha'_m) = \Delta \left( \sum_{j=1}^{n} \frac{1}{n} \Delta^{-1}(p_{jm}, \alpha'_{jm}) \right) \text{ for } m=1, 2, 3, p_m \in S, \text{ and } \alpha'_m \in [-0.5,0.5). \tag{4.2} \]

\[(u_m, \alpha_m) \text{ and } (p_m, \alpha'_m) \text{ respectively denote the aggregate ratings of performance and the grade of importance on infrastructure dimensions in the form of linguistic 2-tuples.} \]

**Step I-3: Second stage assessment.** Both the grade of importance and the rating of performance aggregated in the second stage on each infrastructure dimension should be evaluated to determine the degree of infrastructure capability. According to the operator \( \hat{B}^c \) with equation (2.5), the infrastructure capability represented by linguistic 2-tuples can be expressed as follows:

\[
(u, \alpha) = \Delta \left( \sum_{m=1}^{3} \left[ \Delta^{-1}(p_m, \alpha'_m) \times \Delta^{-1}(u_m, \alpha_m) \right] \right) \text{ for } u \in S; \alpha \in [-0.5,0.5). \tag{4.3} 
\]

The linguistic label \( u \) represents the infrastructure capability according to the assessments of \( n \) experts. Similarly, the process capability can be computed through the above method. According to these two aspects, whether organization managers must improve KMC is thus determined.

### 5. Practical Example

Founded in 1986, the NSFC is the largest government funding agencies in China with the primary aim to promote basic and applied research. There are seven scientific departments, four bureaus, one general office and three associated units at NSFC. The scientific departments are the decision units responsible for the selection and management of projects. They are classified according to the scientific research areas, e.g. mathematical and physical sciences, chemical sciences, life sciences, earth sciences, engineering and material sciences, information sciences, and management sciences, respectively. Departments are further divided into 40 divisions with different focus on specific disciplines [40, 41].

Every year, the NSFC receives more than 53,000 proposals from over 1,400 universities/research institutions in China. The project selection process is coordinated by the top managers of NSFC and is accomplished by the seven scientific departments as well as their divisions. The overall project selection task is decomposed and assigned to departments, and departments further decompose their tasks and assign to divisions. Division managers then assign external reviewers and experts to evaluate proposals [40, 41]. Project selection in NSFC is complicated and knowledge intensive. The task can be hardly completed without effective KM support. So, it is very important for NSFC to know its KMC, which can provide the direction for NSFC to take measures to improve its KMC continuously.

In order to evaluate the KMC of NSFC, three concerned groups of respondents, including project applicants, external reviewers and NSFC managers are invited to give assessments to NSFC’s KMC. There are three respondents in each group. Firstly, the mission and objective, and KM strategy of NSFC should be stated clearly. Secondly, the dimensions of KMC are explained to respondents in great detail, in order that respondents can provide object and precise answers as possible as they can. Then all respondents are requested to fill in a questionnaire (see the Appendix A). Their opinions on the KMC of NSFC can be transformed
The performance of acquisition, conversion, application and security is as follows: the aggregated parameters obtained from the respondents, and

\[
(u_{jm})_3 \times 3 = \begin{bmatrix} M & ML & M & ML & L & ML & MH & M & MH \\ L & M & ML & VL & ML & L & ML & MH & M \\ ML & ML & VL & L & L & DL & M & M & L \end{bmatrix}
\]

\[
\Rightarrow \begin{bmatrix} (S_4,0) & (S_3,0) & (S_3,0) & (S_2,0) & (S_3,0) & (S_4,0) & (S_4,0) \\ (S_2,0) & (S_4,0) & (S_3,0) & (S_1,0) & (S_3,0) & (S_2,0) & (S_3,0) \end{bmatrix},
\]

\[
(p_{jm})_3 \times 3 = \begin{bmatrix} H & VH & H & MH & H & MH & VH & DH & VH \\ VH & VH & DH & H & H & VH & DH & DH & H \\ H & MH & MH & MH & M & M & VH & H & H \end{bmatrix}
\]

\[
\Rightarrow \begin{bmatrix} (S_6,0) & (S_7,0) & (S_6,0) & (S_5,0) & (S_6,0) & (S_5,0) & (S_8,0) & (S_7,0) \\ (S_7,0) & (S_8,0) & (S_6,0) & (S_5,0) & (S_7,0) & (S_8,0) & (S_8,0) \end{bmatrix}.
\]

Suppose the opinions of experts have the equal importance. According to the operator $\bar{B}^e$, the aggregated parameters obtained from the respondents’ linguistic data can be obtained as follows:

\[
(u_m, \alpha_m) = \begin{bmatrix} (M,-0.33) \\ (ML,0) \\ (L,0.33) \end{bmatrix} \quad \text{and} \quad (p_m, \alpha_m) = \begin{bmatrix} (H,0.33) \\ (Vh,0) \\ (MH,0.33) \end{bmatrix} \quad \text{for} \quad m=1, 2, 3.
\]

Both the grade of importance and the rating of performance aggregated above on each infrastructure dimension should be evaluated to determine the degree of infrastructure capability. According to the operator $\hat{B}^e$, the infrastructure capability represented by linguistic 2-tuples can be obtained as follows:

\[
(u, \alpha) = (ML, 0.04).
\]

Therefore, ML is the group linguistic label for infrastructure capability, and the performance of technology, structure and culture is M, ML and L, respectively. Through the same method, we can get the group opinion on process capability that is MH, and the performance of acquisition, conversion, application and security is H, M, H and MH, respectively.

Table 5

<table>
<thead>
<tr>
<th>KM capabilities</th>
<th>Dimensions</th>
<th></th>
<th>External reviewers’ opinion</th>
<th></th>
<th>Rating of performance</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Grade of importance</td>
<td>Rating of performance</td>
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<td>$R_1$</td>
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<td>$R_3$</td>
<td>$R_1$</td>
<td>$R_2$</td>
<td>$R_3$</td>
</tr>
<tr>
<td>Infrastructure capability</td>
<td>$X_1$</td>
<td>H</td>
<td>VH</td>
<td>H</td>
<td>M</td>
<td>ML</td>
<td>M</td>
</tr>
<tr>
<td></td>
<td>$X_2$</td>
<td>VH</td>
<td>VH</td>
<td>DH</td>
<td>L</td>
<td>M</td>
<td>ML</td>
</tr>
<tr>
<td></td>
<td>$X_3$</td>
<td>H</td>
<td>MH</td>
<td>MH</td>
<td>ML</td>
<td>VL</td>
<td></td>
</tr>
<tr>
<td>process capability</td>
<td>$Y_1$</td>
<td>MH</td>
<td>DH</td>
<td>MH</td>
<td>H</td>
<td>MH</td>
<td>H</td>
</tr>
<tr>
<td></td>
<td>$Y_2$</td>
<td>DH</td>
<td>VH</td>
<td>MH</td>
<td>M</td>
<td>MH</td>
<td>M</td>
</tr>
</tbody>
</table>

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Now, the KMC of NSFC is clear for concerned managers. The overall opinion on infrastructure capability of NSFC is ML (More or less low), while the overall opinion on process capability of NSFC is MH (More or less high). Evidently, the former is inferior to the latter. Therefore, the performance of culture is the poorest. So, the managers of NSFC can know the priority of dimensions to be improved. Therefore they can take measures to enhance the KMC effectively and efficiently.

6. Conclusion

The proposed method makes use of the linguistic 2-tuple, it has the advantages of avoiding information loss and distortion, computing results as linguistic labels, and simplifying the calculation process. It is appropriate for situations in which information may be qualitative, or the precise quantitative information is unavailable or the cost of its computation is too high. Moreover, the method seems to be complex, but the calculation process and principle are actually very easy. The comparative analyses between this fuzzy linguistic method and others are illustrated in detailed in Francisco Herrera’s research [23]. However, the method is limited in that evaluators must perfectly distinguish the set of labels under a similar conception, and must use linguistic labels to express their opinions.

The above model with the group evaluation structure, used to evaluate the degree of KMC of organizations, is very useful in knowledge management initiatives. If the degree of KMC is too low according to the evaluation results, it may have to be improved until acceptable. The dimensions of KMC on which improvements must best be made should be determined.

The model described in this research to evaluate the degree of KMC involves group opinion aggregation and uses the fuzzy linguistic method based on 2-tuple, and therefore the final value is objective and unbiased. Issues of practical importance follow.

(1) Generally, if managers plan to estimate the degree of KMC of their organization, they must be invited to participate in a group of evaluators whose collective experience extends across a broad range of related organizations. Their inputs should be reasonable and unambiguous.

(2) Measuring KMC is strategically important, and must affect the formation of knowledge management strategy, to help an organization keep and sustain competitive advantage.

Appendix A. Survey Questionnaires
The mission and objective, and KM strategy of NSFC are stated clearly.

The contents of KMC are explained in great detail.

Respondents should answer the following questions by use one term from the linguistic sets {definitely low (DL), very low (VL), low (L), more or less low (ML), middle (M), more or less high (MH), high (H), very high (VH) and definitely high (DH)}.

What do you think of the technology infrastructure dealing with projection selection in NSFC?

How do you think the applicability of the structure to operations in NSFC?

Which degree do you think the culture facilitate the KM in NSFC?

How do you think the knowledge acquisition capability in NSFC?

How do you think the knowledge conversion capability in NSFC?

How do you think the knowledge application capability in NSFC?

How do you think the knowledge security capability in NSFC?

References


