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Introducing an Evidential Reasoning Approach for Selecting Knowledge Management Strategies

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Abstract

In a knowledge economy, a key source of sustainable competitive advantage relies on the way to create, share, and utilize knowledge. In order to react to an increasingly competitive business environment, many companies emphasize the importance of Knowledge Management (KM), and base their KM strategy on their unique resources and capabilities. Although numerous works discuss the issues of how to perform a KM strategy and implement it successfully, few have provided methods that can systematically evaluate and model the KM strategy involving several complex factors. In this paper, the evidential reasoning (ER) approach is applied as a method for KM strategy selection. The process of building a multiple criteria decision model of a hierarchical structure is presented, in which both quantitative and qualitative information is represented in a unified manner. The KM strategy selection is then fully investigated using the ER approach in a real case study in Academic Center for Education, Culture and Research (ACECR). Both the advantages of applying this model in practice and the analysis process itself are discussed.

Keywords: Knowledge Management Strategy, Multiple Criteria Decision-making (MCDM), Evidential Reasoning, Evidence Theory

1. Introduction

In today's competitive business environment, Knowledge is recognized as an important tool for sustaining competitive advantage and improving performance (Chang & Chuang, 2011), and therefore Knowledge Management (KM) is increasingly recognized as a significant factor in gaining competitive advantage (Spender and Grant, 1996). To obtain such a competitive advantage, companies must realize how to manage organizational knowledge by expanding, disseminating, and exploiting it effectively (Bierly and Chakrabarti, 1996).

Knowledge is taking on an important strategic role as numerous companies are expecting to effectively perform KM to leverage and transform knowledge into competitive advantage (Desouza, 2003). KM is the organizational optimization of knowledge in achieving enhanced performance through the use of various methods and techniques (Kamara et al., 2002). In addition, KM is a systemic way to manage knowledge in the organizationally specified process of acquiring, organizing and communicating knowledge (Benbya et al., 2004). Today, KM and related strategy concepts are promoted as important components for organizations to survive (Martensson, 2000). In order to implement the KM successfully, here raises a critical issue of how companies can better evaluate and select a favorable KM strategy before that KM implementation. However, although numerous creditable works are devoted to the study of how to build a KM strategy and to execute the KM successfully, few of those have provided methods which can systematically evaluate and model complex factors of the KM strategy. Generally, selecting what kinds of KM strategies to use depends on the different purposes, the limited resources, and even the preferences of companies.

Assessment of knowledge management strategies indicated in several articles. For example, Kamara et al. (2002) described a framework for the selection of an appropriate knowledge management strategy, which was developed as part of the CLEVER (Cross-sectoral Learning in the Virtual enterprise) research project. Wu and Lee (2007) and Percin (2010), separately, developed two methods based on Analytic Network Process (ANP) to evaluate and select knowledge management strategies. Wu (2008) proposed a solution based on a combined ANP and DEMATEL approach to help companies with the need to evaluate and select KM strategies.

When companies need to evaluate and select KM strategies, they are usually faced with considering a large number of complex factors. Typically, the Multiple Criteria Decision Making (MCDM) problem is a problem required to evaluate several alternatives involved in a set of evaluation criteria. Hence, selecting a KM strategy is a kind of MCDM problem, and therefore, it is better to employ MCDM methods for achieving effective problem solving.

MCDM problems that embrace both quantitative and qualitative criteria are very common in practice. When facing such MCDM problems, literature and research show that the following difficulties may be encountered:
• Different types of assessments (e.g. numbers, linguistic terms, and/or stochastic values) depending on the characteristics of the decision criteria (Valls and Torra, 2000);
• Imprecise and missing assessments due to lack of data, shortcomings in expertise, time pressure and/or the decision maker (DM) only willing or able to provide incomplete assessments (Kim and Ahn, 1999), and
• Meaningful and robust aggregation of subjective and objective assessments made on multiple (decision) criteria.

Decision criteria for choosing KM strategies are of both quantitative and qualitative natures, and the aforementioned problems do occur. In the last two decades, the evidential reasoning approach to the problem of decision making with multiple criteria has been offered and developed. It is based on a hierarchical evaluation model and synthetic rules of Dempster–Shafer theory of evidence. Until now, the approach was employed in different fields including Failure Mode and Effects Analysis (Chin et al., 2009; Liu et al., 2011), Consumer Preference Prediction (Wang et al., 2009), Assessment of E-Commerce Security (Zhang et al., 2012), and

Performance Assessment (Fu & Yang, 2012). The aim of this paper is to present an application of the Evidential Reasoning (ER) approach to solve this problem with uncertain, imprecise (incomplete), and/or missing information.

Following this introduction, the literature and concept of knowledge management strategy will be summarized. Then, a brief description of ER approach and evidence theory will be given. After that, use of ER approach for KM strategies selection will be explained and discussed in detail. A real example for KM strategy selection in Kermanshah branch of Academic Center for Education, Culture and Research (ACECR) illustrates application of the ER technique. The results and discussion will follow. The conclusion will include the advantages and disadvantages of the method in practice.

2. Knowledge Management Strategy

KM can be defined as the process for acquiring, storing, diffusing and implementing both tacit and explicit knowledge inside and outside the organization's boundaries with the purpose of achieving corporate objectives in the most efficient manner (Magnier-Watanabe and Seno 2008). Moreover, KM can be defined as a process of managing tacit and explicit knowledge in the organization in order to increase competitive advantage (Yip et al., 2010). It is widely recognized that knowledge is an essential strategic resource for a firm in retaining sustainable competitive advantage. As knowledge is created and disseminated throughout the firm, it has the potential to contribute to the firm's value by enhancing its capability to respond to new and unusual situations. There is growing evidence that firms are increasingly investing in knowledge management initiatives and establishing KM systems in order to acquire and better exploit this resource (Sarvary, 1999).

The growing importance of knowledge as a critical resource has encouraged managers to pay greater attention to the firms' KM strategies. Appropriate KM strategies are important to ensure that alignment of organizational process, culture, and the KM-related Information Technology (IT) deployment yields effective knowledge creation, sharing, and utilization (Zack, 1999). Nevertheless, adoption and implementation of KM strategy in practice is not so straight forward due to many different internal and external factors to the company. On the other hand, selecting the appropriate KM strategy is significant to its implementation (Pham and Hara, 2009). Sung and Gibson indicate four key factors for accelerating knowledge and technology transfer: communication, distance, equivocality, and motivation (Sung and Gibson, 2005). Yang (2010) examines the impact of knowledge management strategy on strategic performance in Chinese High Technology firms. In this empirical study, he explored how performance-driven strategy and knowledge management-based competence moderates the relationship between knowledge management strategy and perceived strategic performance. Choi and Jong (2010) using event study methodology, addressed the benefit of KM strategies by exploring how KM strategies influence a firm's market value. They evaluated the cumulative abnormal returns for KM strategies announced by US\\ firms during 1998 to 2003.

In order to improve these KM initiatives and link them to business strategy, some researchers suggest a process-oriented knowledge management approach to strategy to bridge the gap between human- and technology-oriented KM (Maier and Remus, 2003). Moreover, KM strategies are divided into two types: Codification Strategy, and Personalization Strategy (Hansen et al., 1999). Most importantly, in the practice of modeling, evaluating, and selecting KM strategy, it is necessary to take account of different conceptual dimensions and the procedure for KM strategy formulation. There are four different proposed conceptual dimensions of KM strategy including epistemological dimension, ontological dimension, systemic dimension, and strategic dimension (Campos and Sanchez, 2003).

Although numerous works discuss the issues of how to perform and successfully implement a KM strategy it, few have provided methods that can systematically evaluate and model the KM strategy involving several complex factors. Selecting what kinds of KM strategies to use is dependent on the company's desired purposes, limited resources, and even the company's preferences. Hence, the KM strategy selection is a kind of MCDM problem, which requires MCDM methods for effective problem solving. MCDM problems that embrace both quantitative and qualitative criteria are very common in practice. Decision criteria for choosing KM strategies are of both quantitative and qualitative natures, and the aforementioned problems do occur.

3. Evidential Reasoning Approach

Evidential reasoning approach consists of a hierarchical evaluation model and synthetic rules of Demster-Shafer theory of evidence. Yang and Sing (1994) introduced the approach for the first time; hence, there were numerous attempts to extend its theory (Yang & Zu, 2002a; Yang & Zu, 2002b). Yang et al. developed it through two possible and fuzzy stages. Chin et al. (2008) utilized the approach in a state of making decision of a group for product project screening. So far, researchers avail themselves of this method in a variety of applications such as Failure Mode and Effects Analysis (Chin et al., 2009; Liu et al., 2011), Consumer Preference Prediction (Wang et al., 2009), Assessment of E-Commerce Security (Zhang et al., 2012), and Performance Assessment (Fu & Yang, 2012).

During the assessment, we usually encountered cases where sufficient information for the assessment process was not available for the decision maker. The evidential reasoning approach is proposed using the concept of the degree of assurance and within a framework with operable methodology in the face of such circumstances. The degree of assurance can be interpreted as a degree of prediction of an expected outcome through a particular standard (Yang & Zu, 2002a). The reason for using this is that it is invariably of little use or at least applicability to give an accurate and reliable assessment at the time of evaluation. The reasons for this can be associated with the nature of experimental knowledge as well as lack of the decision maker's adequate knowledge and experience during assessment.

During assessment, intellectual capital received no clear and assuring assessment, may be because the decision maker or assessor has to deal with a great amount of assessment through quantitative and qualitative criteria. With such circumstances, a clear and assuring assessment seems difficult and in some cases impossible.

4. Dempster–Shafer Theory of Evidence

The evidence theory was first developed by Dempster (1967) in the 1960s. His work was later extended and refined by Shafer (1976) in the 1970s. Therefore, this theory is also called the Dempster–Shafer theory of evidence or the D–S theory in abbreviation. The theory is related to the Bayesian probability theory in the sense that they both deal with subjective beliefs. However, the evidence theory includes the Bayesian probability theory as a special case, the biggest difference being in that the former is able to deal with ignorance, while the latter is not, and its subjective beliefs are also required to obey probability rules.

The evidence theory has been widely applied in many areas such as Artificial Intelligence (AI), Expert Systems, Pattern Recognition, Information Fusion, Database and Knowledge Discovery, Multiple Attribute Decision Analysis (MADA), and Audit Risk Assessment etc. (Denoeux, 2000).

Suppose $H = \{H_1, H_2, \dots, H_n\}$ be a collectively exhaustive and mutually exclusive set of hypotheses or propositions, which is called the frame of discernment. A basic probability assignment (bpa) (also called a belief structure) is a function $m: 2^H \longrightarrow [0\,,1]$ namely a mass function and satisfies:

$$m(\Phi)=0 \quad \text{and} \quad \sum_{A \subseteq H} m(A)=1 \qquad (1)$$

where Φ is the null set, A is any subset of H, and 2^H is the power set of H, which consists of all the subsets of H, i.e.

$$2^H = \{\Phi, \{H_1\}, \dots, \{H_1, H_2\}, \dots, \{H_1, H_N\}, \dots, H\} \qquad (2)$$

The assigned probability (also called probability mass) $m(A)$ measures the belief exactly assigned to A and represents how strongly the evidence supports A. All the assigned probabilities sum to unity and there is no belief in the empty set (Φ). The assigned probability to H, i.e. $m(H)$, is called "the degree of ignorance". Each subset $\{A \subseteq H | m(A) > 0\}$ is called "a focal element of m". All the related focal elements are collectively called "the body of evidence".

A belief measure, Bel, and a plausibility measure, Pl, is associated with each bpa, and they are both functions: $2^H \longrightarrow [0\,,1]$ defined by the following equations, respectively:

$$Bel(A) = \sum_{B \subseteq A} m(B) \qquad (3)$$

$$Pl(A) = \sum_{A \cap B \neq \Phi} m(B) \qquad (4)$$

where A and B are subsets of H. Bel(A) represents the exact support for A (i.e. the belief of the hypothesis of A being true); Pl(A) represents the possible support for A (i.e. the total amount of belief that could be potentially placed in A). $[Bel(A), Pl(A)]$ constitutes the interval of support for A and can be seen as the lower and upper bounds of the probability to which A is supported. The two functions can be connected by the following equation:

$$Pl(A) = 1 - Bel(\bar{A}) \tag{5}$$

where $\bar{A}$ denotes the complement of A. The difference between the belief and the plausibility of a set A describes the ignorance of the assessment for the set A.

Since $m(A)$, $Bel(A)$ and $Pl(A)$ are in one-to-one correspondence, they can be seen as three facets of the same piece of information. There are several other functions such as commonality and doubt functions, which can also be used to represent evidence and provide flexibility to match a variety of reasoning applications.

The core of the evidence theory is Dempster's rule of combination, by which evidence from different sources is combined or aggregated. The rule assumes that information sources are independent and uses the so-called orthogonal sum to combine multiple belief structures:

$$m = m_1 \oplus m_2 \oplus \dots \oplus m_K \tag{6}$$

where $\oplus$ represents the operator of combination. With two belief structures m_1 and m_2, Dempster's rule of combination is defined as follows:

$$[m_1 \oplus m_2](C) = \begin{cases} 0, & C = \Phi, \\ \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \Phi} m_1(A) m_2(B)}, & C \neq \Phi, \end{cases} \tag{7}$$

where A and B are both focal elements and $[m_1 \oplus m_2](C)$ itself is a bpa. The denominator$1 - \sum_{A \cap B = \phi} m_1(A) m_2(B)$ is denoted by k and called "the normalization factor". $\sum_{A \cap B = \phi} m_1(A) m_2(B)$ is called "the degree of conflict" and measures the conflict between the pieces of evidence. The division by k is called "normalization".
Dempster's rule of combination proved to be both commutative and associative (i.e. $m_1 \oplus m_2 = m_2 \oplus m_1$ (commutativity) and $(m_1 \oplus m_2) \oplus m_3 = m_1 \oplus (m_2 \oplus m_3)$ (associativity)). These two properties show that evidence can be combined in any order. Therefore, in the case of multiple belief structures, evidence can be combined in a pairwise manner.

5. The ER Approach for Selecting KM Strategies

The ER approach for KM strategies selection consists mainly of seven key sections, which are: 1) Definition of the KM problem; 2) Identification of possible KM strategies; 3) Identification of KM strategies assessment factors; 4)The ER distributed modeling framework for KM strategies' assessments; 5) Recursive and analytical ER algorithms for aggregating multiple identified KM strategies assessment factors, and 6) Utility-interval-based ER ranking method that is designed to systematically compare and rank alternatives/options. Each part will be described in detail in this section.

5.1. Definition of KM Problem

The aim of this step is to define the overall KM problem within a business context, and involves a description of the perceived problem and identifying its underpinning business drivers. The characteristics of the knowledge under consideration are defined, and potential users and sources of this knowledge are identified. The probable enablers and inhibitors for identified users and sources, and the potentially relevant KM processes (e.g. creation and transfer of knowledge) are also identified. The output of this stage is a clarified KM problem and a set of knowledge management issues emanating from the problem.

5.2. Organizational Learning and Identification of Possible KM Strategies

In the rapid change economics volatility and uncertainty, many organizations are striving to survive and remain competitive. In order to develop and perform, Organizational Learning (OL) has been regarded as one of the strategic means of archiving long-term organizational success. The term organizational learning itself is described as “the process of creation and steadily development of organizational knowledge basis, which is the foundation for generation of change and developing strategies” (Liao and Wu, 2010).

Due to the complex and diverse environment of firms and increasing demands of stakeholders, organizational learning is seen as basis approach, which will satisfy the needs and requirements of these parties. The task of an innovative organization is to generate new knowledge by:
• Continual improvement of all corporate activities;
• Development of new applications/services out of corporate success, and
• Permanent innovation as an organized process.
In summary, permanent innovation requires organized (suitable) processes and an organizational fit within its environment.
The overall basis for establishing a learnable organization in a specific environment is described by the approach of Takeuchi and Nonaka (1995). The required factors include:
• *Intention* (establishing of a strategy and offering management tools to implement this process);
• *Autonomy* (enabling self-managed action on the individual level as far as possible),
• *Employee turnover and creative chaos* (generation of reciprocal effects between stakeholders and organizational parts of the firm);
• *Redundancy* (fostering existence of redundant knowledge by operating across research borders), and
• *Essential variation* (allowing internal diversity to meet strategic organizational goals).

The positive identification of the organizational learning basis is a fundamental step in creating KM strategies. This allows the creation of some strategies for the firm.

5.3. Identification of KM Strategy' Assessment Factors

To assess KM strategies, first it is required to carefully identify all factors that need to be assessed. It is very difficult to examine and assess all of these elements on a regular basis. The key issue in this step is to ensure that all KM strategy factors that need to be considered are included, while those requiring extensive identification and evaluation effort but having little impact on KM strategies are considered. Fig. 1 shows the typical KM strategy assessment factors applied by Wu and Lee (2007). Simple and descriptive checklist approaches, including questionnaire checklists, provide a structured approach for identifying KM strategies' factors for consideration. Usually, an initial list of factors of potential relevance may be first determined through extensive literature review, review of other recent projects of KM strategies selection on similar works. And then, a selected list of pertinent factors for a given project can be screened through interdisciplinary team discussions, professional judgments, criteria questions, and so on.

5.4. Determination of Weights and Assessment Grades

The identified factors usually have different functions and play different roles in a KM strategy. Some of them are crucial to KM strategy; some are very important, and some are important, but not very important or crucial compared with others. Different KM strategies factors are therefore of different relative importance, which should be considered in the assessment of KM strategy. There are many different ways such as pairwise comparison matrix method (or called AHP or Eigenvector method) (Saaty, 1998), Delphi method (Chang, et al. 2000; Curtis, 2004), and so on, which can all be used to determine the relative weights of the identified strategy factors. Fig. 1 shows the relative weights of the six identified KM strategy factors.

In order to evaluate the identified factors, assessment standards are absolutely necessary and need to be defined. Evaluation grades provide a complete set of distinct standards for assessing the qualitative attributes in question. In accomplishing this objective, an important aspect to analyze is the level of discrimination among different countings of evaluation grades or, in other words, the cardinality of the set used to express the information. The cardinality of the set must be small enough so as not to impose useless precision on the users, and must be rich enough in order to allow discrimination of the assessments in a limited number of degrees.

5.5. The ER Distributed Modeling Framework for KM Strategy Assessment

After determining assessment grades, each identified strategy factor can therefore be properly assessed according to the predefined assessment standards. Without loss of generality, suppose $H_1, \ldots, H_N$ are *N* defined assessment grades or ratings, which are mutually exclusive and collectively exhaustive. Note that all the ratings will be viewed and treated in this paper as assessment grades rather than numerical values (cardinal data). These *N* assessment grades constitute the frame of discernment denoted as:

$$H = \{H_1, \dots, H_N\} \tag{8}$$

Suppose there are *M* KM strategies $S_l\ (l = 1, \dots, M)$ to be assessed in terms of L identified strategy factors $F_i\ (i = 1, \dots, L)$, which are called "basic strategy factors" and form a hierarchy like Fig. 1. For illustrative purposes, only a two-level hierarchy is assumed here. However, the ER approach introduced in this paper is applicable to multiple-level hierarchies. This will be illustrated through a real case study later.
Suppose the relative weights of the L strategy factors are given by $W = (w_1, \dots, w_L)$, which are normalized to satisfy the following condition:

$$\sum_{i=1}^{L} w_i = 1 \quad and \quad w_i \geq 0, \quad i = 1, \dots, L \tag{9}$$

If a strategy S_l is assessed on a strategy factor F_i to a grade H_n with a belief degree of $\beta_{n,i}(S_l)$, then we denote this by $S\big(F_i(S_l)\big) = \{\big(H_n, \beta_{n,i}(S_l)\big), n = 1, \dots, N\}$, which is a distributed assessment and is referred to as a belief structure, where H_n represents the *n*-th element (assessment grade) of the set *H*. The distributed assessment allows strategy experts to assess each strategy factor to more than one assessment grade if necessary.

The distributed modeling framework of the ER approach makes it possible to capture the diversity of assessment information and is well suited to modeling strategy condition assessment problems. In a distributed assessment, it is required that $\beta_{n,i}(S_l) \geq 0$ and $\sum_{n=1}^{N} \beta_{n,i}(S_l) \leq 1$. If $\sum_{n=1}^{N} \beta_{n,i}(S_l) = 1$, the assessment is said to be complete; otherwise, it is said to be incomplete. If $\sum_{n=1}^{N} \beta_{n,i}(S_l) = 0$, the assessment is said to be totally ignorant.

The assessment results of every KM strategy on each strategy factor are represented by the following belief decision matrix:

$$D = \big(S\big(F_i(S_l)\big)\big)_{L \times M} \tag{10}$$

which differs from the traditional decision matrix in that each element of the belief decision matrix D is a distribution rather than a single value. Based on the above belief decision matrix, all the distributed assessment information can be aggregated in a rational and effective way using ER algorithms.

5.6. Recursive and Analytical ER Algorithms

One simple approach for attribute (strategy factor) aggregation is to transform a belief structure into a single score and then aggregate attributes on the basis of the scores using traditional methods such as the additive utility function approach. However, such transformation would hide performance diversity shown in a distribution assessment, leading to the possible failure of identifying strengths and weaknesses of an alternative KM strategy on higher-level attributes. In the ER approach, attribute aggregation is based on evidential reasoning rather than directly manipulating (e.g. adding) scores. In other words, the given assessments of alternatives on the individual basic attributes are treated as evidence, and which evaluation grades the general attribute should be assessed to is treated as hypotheses (Yang and Singh, 1994). Dempster's evidence combination rule is then employed and revised to create a novel process for such attribute aggregation (Yang, 2001; Yang and Xu, 2002). The revision of the rule is necessary due to the need to handle conflicting evidence and follow common sense rules for attribute aggregation in MADA. Detailed analysis and rationale on development of the attribute aggregation process can be found in Yang (2001) and Yang and Xu (2002). The process is briefly described in the following steps.

First, a degree of belief given to an assessment grade H_n for a strategy S_l on a strategy factor F_i is transformed into a basic probability mass by multiplying the given degree of belief by the relative weight of the strategy factor using the following equations:

$$m_{n,i} = m_i(H_n) = w_i\beta_{n,i}(S_l), \;\; n = 1, \dots, N; \quad i = 1, \dots, L \tag{11}$$

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i} = 1 - w_i \sum_{n=1}^{N} \beta_{n,i}(S_l), \;\; i = 1, \dots, L \tag{12}$$

$$\bar{m}_{H,i} = \bar{m}_i(H) = 1 - w_i, \;\; i = 1, \dots, L \tag{13}$$

$$\tilde{m}_{H,i} = \tilde{m}_i(H) = w_i(1 - \sum_{n=1}^{N} \beta_{n,i}(S_l)), \;\; i = 1, \dots, L \tag{14}$$

with $m_{H,i} = \bar{m}_{H,i} + \tilde{m}_{H,i}$ and $\sum_{i=1}^{L} w_i = 1$.

Note that the probability mass assigned to the whole set H, $m_{H,i}$ which is currently unassigned to any individual grade is split into two parts: $\bar{m}_{H,i}$ and $\tilde{m}_{H,i}$, where $\bar{m}_{H,i}$ is caused by the relative importance of the attribute F_i, and $\tilde{m}_{H,i}$ by the incompleteness of the assessment on F_i.

The second step is to aggregate the attributes by combining the basic probability masses generated above, or reasoning based on the given evidence (Yang and Singh, 1994). Due to the assumptions that evaluation grades are mutually exclusive and collectively exhaustive, and that assessments on a basic attribute are independent of assessments on other attributes, or utility independence among attributes, Dempster's combination rule can be directly applied to combine the basic probability masses in a recursive fashion. In the belief decision matrix framework, the combination process can be developed into the following recursive ER algorithm (Yang, 2001; Yang and Xu, 2002a):

$$\{H_n\} : m_{n,I(i+1)} = K_{I(i+1)}\left[m_{n,I(i)}m_{n,i+1} + m_{n,I(i)}m_{H,i+1} + m_{H,I(i)}m_{n,i+1}\right], \tag{15}$$

$$m_{H,I(i)} = \bar{m}_{H,I(i)} + \tilde{m}_{H,I(i)}, \;\; n = 1, \dots, N \tag{16}$$

$$\{H\} : \tilde{m}_{H,I(i+1)} = K_{I(i+1)}\left[\tilde{m}_{H,I(i)}\tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)}\bar{m}_{H,i+1} + \bar{m}_{H,I(i)}\tilde{m}_{H,i+1}\right], \tag{17}$$

$$\{H\} : \bar{m}_{H,I(i+1)} = K_{I(i+1)}\left[\bar{m}_{H,I(i)}\bar{m}_{H,i+1}\right], \tag{18}$$

$$K_{I(i+1)} = \left[1 - \sum_{n=1}^{N} \sum_{\substack{t=1 \\ t \neq n}}^{N} m_{n,I(i)} m_{t,i+1}\right]^{-1}, \quad i = 1, \dots, L-1 \tag{19}$$

$$\{H_n\}: \beta_n = \frac{m_{n,I(L)}}{1 - \bar{m}_{H,I(L)}}, \quad n = 1, \dots, N, \tag{20}$$

$$\{H\}: \beta_H = \frac{\tilde{m}_{H,I(L)}}{1 - \bar{m}_{H,I(L)}} \tag{21}$$

In the above equations, $m_{n,I(i)}$ denotes the combined probability mass generated by aggregating i attributes; $m_{n,I(i)} m_{n,i+1}$ measures the relative support for the hypothesis that the general attribute should be assessed to the grade H_n by both the first i attribute and the $(i + 1)$th attribute; $m_{n,I(i)} m_{H,i+1}$ measures the relative support for the hypothesis by the first i attributes only; $m_{H,I(i)} m_{n,i+1}$ measures the relative support for the hypothesis by the $(i + 1)$th attribute only. It is assumed in the above equations that $m_{n,I(1)} = m_{n,1}$ $(n = 1,\dots,N)$, $m_{H,I(1)} = m_{H,1}$, $\bar{m}_{H,I(1)} = \bar{m}_{H,1}$ and $\tilde{m}_{H,I(1)} = \tilde{m}_{H,1}$. Note that the aggregation process does not depend on the order in which attributes are combined.

β_n and β_H represent the belief degrees of the aggregated assessment, to which the general attribute is assessed to the grades H_n and H, respectively. The combined assessment can be denoted by $S(y(S_l)) = \{(H_n, \beta_n(S_l)), n = 1,\dots,N\}$. It has been proved that $\sum_{n=1}^{N} \beta_n + \beta_H = 1$. Yang and Xu also put forward four axioms and proved the rationality and validity of the above recursive ER algorithm (Yang and Xu, 2002a).

The nonlinear features of the above aggregation process were also investigated in detail (Yang and Xu, 2002b). In the above ER algorithm, Eqs. (15)–(19) are the direct implementation of Dempster's evidence combination rule within the belief decision matrix; the assignment of the basic probability masses shown in Eqs. (11)–(14) and the normalization of the combined probability masses shown in Eqs. (20) and (21) are developed to ensure that the ER algorithm can process conflicting evidence rationally, and satisfy common sense rules for attribute aggregation in MADA (Yang and Xu, 2002a).

5.7. The Utility Interval Based ER Ranking Method

In order to compare or rank M KM strategies in terms of their factor assessments, the ER approach introduces the concepts of maximum, minimum and average expected utilities. Suppose the utility of an assessment grade H_n is denoted by $u(H_n)$. The expected utility of the aggregated distributed assessment $S\big(y(S_l)\big)$ is defined as (Yang, 2001):

$$u\Big(S\big(y(S_l)\big)\Big) = \sum_{n=1}^{N} \beta_n (S_l) u(H_n). \tag{22}$$

It has been proved that the aggregated belief degree $\beta_n(S_l)$ reflects the lower bound of the likelihood that S_l is assessed to H_n, while the corresponding upper bound of the likelihood is given by $(\beta_n(S_l)+\beta_H(S_l))$, which leads to the establishment of a utility interval if the assessment is incomplete.

Suppose the least preferred assessment grade is H_1, which has the lowest utility and the most preferred assessment grade is H_n, which has the highest utility. The maximum, minimum and average expected utilities of S_l are therefore given as:

$$u_{max}(S_l) = \big(\beta_N(S_l)+\beta_H(S_l)\big)u(H_n) + \sum_{n=1}^{N-1}\beta_n(S_l)u(H_n), \tag{23}$$

$$u_{min}(S_l) = \sum_{n=2}^{N}\beta_n(S_l)u(H_n) + \big(\beta_1(S_l)+\beta_H(S_l)\big)u(H_1) \tag{24}$$

$$u_{avg}(S_l) = \frac{u_{max}(S_l)+u_{min}(S_l)}{2} \tag{25}$$

If $u(H_1) = 0$, then $u\Big(S\big(y(S_l)\big)\Big) = u_{min}(S_l)$; if all the original assessments $S\big(C_i(S_l)\big)$ in the belief matrix are complete, then $\beta_H(S_l) = 0$ and $u\Big(S\big(y(S_l)\big)\Big) = u_{min}(S_l) = u_{max}(S_l) = u_{avg}(S_l)$. According to the maximum/minimum utilities and the corresponding utility interval, the ranking of two KM strategies can be made as follows. If $u_{min}(S_l) \geq u_{max}(S_k)$, then the KM strategy S_l is said to be preferred the KM strategy S_k; if $u_{min}(S_l) = u_{min}(S_k)$ and $u_{max}(S_l) = u_{max}(S_k)$, then the KM strategy S_l is said to be indifferent to the KM strategy S_k. In other cases, the degree of preference of S_l over S_k can be computed by

$$P(S_l > S_k) = \frac{\{\max[0, u_{max}(S_l)-u_{min}(S_k)] - \max[0, u_{min}(S_l)-u_{max}(S_k)]\}}{\{[u_{max}(S_l)-u_{min}(S_l)] + [u_{max}(S_k)-u_{min}(S_k)]\}} \tag{26}$$

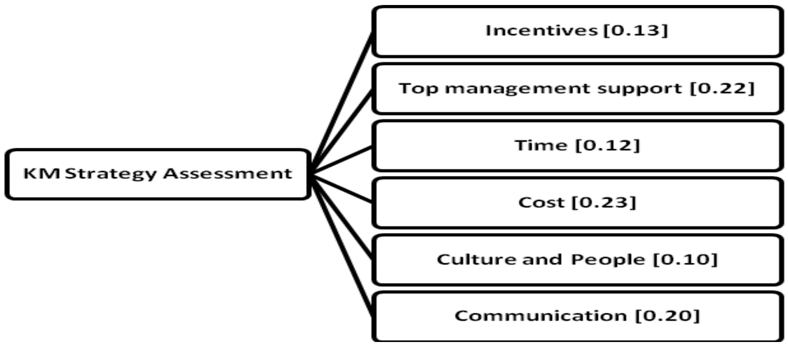
If $P(S_l > S_k) > 0.5$, then the KM strategy S_l is said to be superior to the KM strategy S_k to the degree of $P(S_l > S_k)$; if $P(S_l > S_k) = 0.5$, then the KM strategy S_l is said to be indifferent to the KM strategy S_k; If $P(S_l > S_k) < 0.5$, then the KM strategy S_l is said to be inferior to the KM strategy S_k to the degree of $1 - P(S_l > S_k)$.

It is worth pointing out that the expected utility is not the only way of ranking alternatives. It can also be replaced by other indices such as expected score. In this situation, $u(H_n)$ represents the score of the grade H_n $(n = 1, \ldots, N)$.

6. Application of ER in a Real Case Study

In this section, a real case study for Kermanshah branch of Academic Center for Education, Culture and Research (ACECR) is used to show that KM strategies can be evaluated more efficiently and more flexibly using a distributed modeling framework, and how the distributed assessment information can be aggregated using the proposed algorithm of the ER approach. The set of decision criteria for KM strategy assessment applied to this study, and the set of criteria weights calculated using the pairwise comparison matrix method (or called AHP or Eigenvector method) are shown in Fig. 1.

Figure 1: Hierarchy for KM strategy assessment



In this paper, we suppose a simple hierarchical structure consisting of one level with a general attribute. However, the ER approach can aggregate factors step-by-step from the bottom level to the top level. Each group of the bottom-level factors sharing the same medium-level factor is first aggregated to generate an assessment for the corresponding medium-level factor. Once the assessments for a group of medium-level factors associated with the same top-level strategy factor are all generated, these assessments are then further aggregated in the same fashion to generate an assessment for the top-level factor.

In this case, there are three strategies: 1) Codification strategy (S_1); 2) Personalization strategy (S_2), and 3) Blend strategy (S_3) that need to be assessed in terms of six strategy factors. These factors are: 1) Incentives (F_1); 2) Top management support (F_2) 3) Time (F_3); 4) Cost (F_4); 5) Culture and People (F_5), and 6) Communication (F_6). Some of these factors may only be assessable using subjective judgments, while the remainder might be assessed numerically. For example, the factor “Incentives” is a qualitative attribute requiring subjective assessment (e.g. against a number of grades that could be used for this purpose). Suppose that the Decision Maker (DM) wants to classify KM strategies being evaluated into the following grades: “worst”, “bad”, “average”, “good”, and “excellent” at the top level. Next, the DM is required to define assessment grades for the main criteria. The outcomes for each criterion may be expressed in different terms in the mind of the DM who may wish to use the most appropriate vocabulary to evaluate (and represent) each criterion. Therefore, the DM may well use the same set of grades as defined for the goal of the problem for some main criteria, and develop new sets of grades for other main criteria. In Table 1, the DM used four grades for the criterion “Communication (F_6)” whilst the other main criteria were evaluated with a set of five grades each, using different wordings. The use of different grades facilitates data collection and allows capture of the DM's preferences, experience, intuition or beliefs, and implies that the DM is not manipulated by the method or decision analyst who may help them during the decision process. This is because they use their own expressions to evaluate decision criteria. Although this may increase ambiguity, uncertainty, or imprecision in the data, the ER approach facilitates this through rule and utility based knowledge transformation, which will be explained in the subsequent sections.

Table 1: Assessment grades defined by the DM for the main criteria

Main Criteria (Strategy factors)	**Assessment Grades**				
Incentives (F_1)	Poor	Average	Good	Very good	Excellent
Top management support (F_2)	Very low	Low	Average	High	Very high
Time (F_3)	Quantity(months)				
Cost (F_4)	Quantity(dollars)				
Culture and People (F_5)	Very Poor	Poor	Average	Good	Very good
Communication (F_6)	Critical	Poor	Good	Excellent	

A DM may then state that a strategy's Incentives (e.g. Personalization strategy (S_2)) is 30% very good and 60% excellent) represented by {(very good, 0.3), (excellent, 0.6)}. In this statement, very good and excellent are the two distinctive grades, and the numbers 30 and 60 are called the "degrees of belief" of the DM. Table 2 shows the assessment information for the three strategies, which illustrates that some strategy factors are assessed against one grade while the others are assessed against two two grades, each to a belief degree of less than or equal to one. Few of the strategy factor assessments are incomplete or totally ignorant as highlighted in Table 5, where the assessments of strategy S_1 on Communication (F_6) and the assessment of strategy S_2 on Incentives (F_1) and Culture and People (F_5) are incomplete because their total degrees of belief are 0.8, 0.9 and 0.8, respectively, which are all less than 100%; while the assessment of strategy S_3 on Communication (F_6) is unknown or not available and is therefore totally ignorant because no belief degree is assigned to any assessment grades in this assessment.

Table 2: Assessment of KM strategies based on the six main criteria

Strategy factors [Relative weights]	**Codification strategy (S_1)**	**Personalization strategy (S_2)**	**Blend strategy (S_3)**
Incentives (F_1)[0.13]	{(poor, 0.6), (average, 0.4)}	{(very good,0.3), (excellent,0.6)}	{(good,1.0)}
Top management support (F_2)[0.22]	{(high, 0.45), (very high, 0.55)}	{(average, 1.0)}	{(average, 0.5), (high, 0.5)}
Time (F_3)[0.12]	30	55	40
Cost (F_4)[0.23]	120000	170000	160000
Culture and People (F_5)[0.10]	{(poor, 0.7), (average, 0.3)}	{(good, 0.5), (very good, 0.3)}	{(average, 0.8), (good, 0.2)}
Communication (F_6)[0.20]	{(critical, 0.5), poor, 0.3)}	{(good, 0.75), (excellent, 0.25)}	unknown

Suppose that a DM has made assessments on strategy S_1 regarding those factors as shown in Table 1. This assessment is a mix of quantitative and qualitative evaluation. It needs to be combined and transformed to the associated upper level so that a single and aggregated evaluation index can be found for this upper-level criterion. This transformation can be either rule- or utility-based depending on the decision maker's preference. The transformation process is given in Table 3. This problem consists of six sub criteria, two of which are of quantitative nature. Since KM strategy's sufficiency is evaluated against five verbal grades, all sub criteria assessments need to be transformed to these grades. If the sub criterion is evaluated against the same number of verbal grades as the associated upper-level criterion, then the transformation is straightforward. However, if the number of verbal grades is different, then a rule-based transformation is necessary. Table 3 shows this rule-based transformation.

Table 3: Transformation of Main Criteria Assessments to Upper Level

General attribute /assessment grades	**Worst**	**Bad**	**Average**	**Good**	**Excellent**
Incentives (F_1)	Poor	Average	Good	Very good	Excellent
Top management support (F_2)	Very low	Low	Average	High	Very high
Time (F_3) (months)	70	60	50	40	30
Cost (F_4) (dollars)	200000	180000	160000	140000	120000
Culture and People (F_5)	Very poor	Poor	Average	Good	Very good
Communication (F_6)	Critical	Poor(0.6)	Poor(0.4); Good(0.4)	Good(0.6); Vxcellent(0.2)	Excellent(0.8)

As can be seen from Table 4, the overall assessment of Codification strategy S_1 is assessed to all grades with the degrees of belief of 16.2%, 14.1%, 5%, 9.4% and 52.1%, respectively; Personalization strategy S_2 is assessed to grades 2, 3, 4 and 5 with the degrees of belief of 16.6%, 50.3%, 17.4% and 13.1%, respectively; and strategy S_3 is assessed to grades 3 and 4 with the degrees of belief of 61.9% and 23.6%, respectively. The overall assessments of each three strategies are incomplete due to the incompleteness of their original assessment information. That means there exists a probability of 3.5% for strategy S_1, a probability of 2.6% for strategy S_2, and a probability of 14.5% for strategy S_3, which cannot be precisely assigned to any one of the seven defined assessment grades.

Table 4: Overall Assessment of KM Strategies

KM Strategy	**Grades**					**Unknown**
	Worst	**Bad**	**Average**	**Good**	**Excellent**	
Codification strategy (S_1)	0.162	0.141	0.050	0.094	0.521	0.035
Personalization strategy (S_2)	0	0.166	0.503	0.174	0.131	0.026
Blend strategy (S_3)	0	0	0.619	0.236	0	0.145

In the case that a large number of strategies need to be compared, ranked or prioritized according to their overall conditions, comparisons may not be so straightforward. In this situation, the utility-based ER ranking approach could be used to provide a ranking. Suppose a DM provides the following utilities about the five assessment grades:

$$u(worst) = 0.1 \; ; u(bad) = 0.3 \; ; u(average) = 0.5 \; ; u(good) = 0.8 \; ; u(excellent) = 1$$

The expected utilities of the three strategies can be calculated by Eqs. (22)–(24). Results are shown in Table 5; the expected utilities of strategies S_1, S_2 and S_3 represent different ranges due to the fact that their overall assessments are incomplete. It is also observed that one of the minimum expected utilities is not greater than the other maximum expected utility of strategies; therefore, we generated final ranking by Eq. (25). The final ranking can be generated as $Codification\ strategy \succ Personalization\ strategy \succ Blend\ strategy$, where the symbol ‘‘$\succ$’’ means ‘‘is better than’’.

Table 5: Expected Utilities of the Three KM Strategies

KM Strategy	**Minimum utility**	**Maximum utility**	**Average utility**
Codification strategy (S_1)	0.6814	0.6972	0.7130
Personalization strategy (S_2)	0.5739	0.5857	0.5975
Blend strategy (S_3)	0.5128	0.5780	0.6432

7. Conclusion

In this paper a novel evidential reasoning (ER) approach was developed for KM strategy selection. The seven main steps of implementing the ER approach were illustrated. A Decision Maker (DM) may be willing or able to provide only incomplete, imprecise and vague information because of time pressure, lack of data or shortcomings in expertise when evaluating strategies against a pre-determined set of criteria. In addition, the DM may wish to evaluate intangible criteria by using linguistic variables, which facilitate the processing of raw (normally difficult to represent) data. Thus, there are two problems to address: 1) How to reconcile quantitative and qualitative decision criteria (data)?, and 2) How to deal with incomplete information in a rational way? It is shown that the ER approach is able to tackle these two problems and can help DMs reach a robust decision, although some data may be missing and/or assessments may be incomplete. A further advantage of the method is that uncertainty and risk surrounding the decision problem can be represented through the concept of ‘the *degree of belief*‘. The computer software IDS facilitates the implementation of the ER approach. One of the disadvantages of the method may be that it requires more complicated calculations than some other methods such as MAUT.

A real case study for ACECR was used to illustrate the ER approach for the KM strategy selection. It is shown that the proposed ER approach offers a flexible and effective way of assessing KM strategies. It does not only take into consideration the relative importance of each KM strategy factor, but also allows for KM strategy factors to be rated more realistically and more flexibly. Instead of treating KM strategy assessments as precise numerical numbers, it handles them as assessment grades, which better suit the problems of strategy assessments.

References

Benbya, H., Passiante, G., & Belbaly, N. A. (2004). Corporate portal: a tool for knowledge management synchronization, International Journal of Information Management, 24(3), , 201–220.

Bierly, A., & Chakrabarti, A. (1996). Generic knowledge strategies in the US pharmaceutical industry. Strategic Management Journal, 17, 123–135.

Campos, E. B., & Sanchez, M. P. S. (2003). Knowledge management in the emerging strategic business process: information, complexity and imagination. Journal of Knowledge Management, 7(2), 5–13.

Chang, P. T., Huang, L. C., & Lin, H. J. (2000). The fuzzy Delphi method via fuzzy statistics and membership function fitting and an application to the human resources. Fuzzy Sets and Systems, 112(3), 511–520.

Chang, T. C., & Chuang, S. H. (2011). Performance implications of knowledge management processes: Examining the roles of infrastructure capability and business strategy. Expert Systems with Applications. 38, 6170–6178.

Chin, K. S., Xu, D. L., Yang, J. B., & Lam, J P. K. (2008). Group-based ER–AHP system for product project screening. Expert Systems with Applications, 35, 1909–1929.

Choi, B., & Jong, A. M. (2010). Assessing the impact of knowledge management strategies announcements on the market value of firms. Information & Management, 47, 42–52.

Curtis, I. A., (2004). Valuing ecosystem goods and services: a new approach using a surrogate market and the combination of a multiple criteria analysis and a Delphi panel to assign weights to the attributes. Ecological Economics, 50(3–4), 163–194.

Dempster, A. P. (1967). Upper and lower probabilities induced by a multivalued mapping. Annals of Mathematical Statistics, 38(2), 325–339.

Denoeux, T. (2000). A neural network classifier based on Dempster– Shafer theory. IEEE Transactions on Systems, Man and Cybernetics— Part A: Systems and Humans, 30(2), 131–150.

Desouza, K. C. (2003). Strategic contributions of game rooms to knowledge management: some preliminary insights. Information & Management, 41(1), 63–74.

Fu, C. & Yang, Y. (2012). The combination of dependence-based interval-valued evidential reasoning approach with balanced scorecard for performance assessment. Expert Systems with Applications, 39, 3717–3730.

Hansen, M. T., Nohria, N., & Tierney, T., (1999), What's your strategy for managing knowledge?. Harvard Business Review, 77(2), 106–126.

Kamara, J. M., Anumba, C. J., & Carrillo, P. M. (2002). A CLEVER approach to selecting a knowledge management strategy. International Journal of Project Management, 20(3), 205–211.

Kim, S. H., & Ahn, B. S. (1999). Interactive group decision making procedure under incomplete information., European Journal of Operational Research, 116(3), 498–507.
Liao, S. H., & Wu, C. C., (2010). System perspective of knowledge management, organizational learning, and organizational innovation. Expert Systems with Applications, 37, 1096–1103.
Liu, H. C., Liu, L., Bian, O. H., Lin, Q. L., Dong, N., & Xu, P. C. (2011). Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory. Expert Systems with Applications, 38, 4403–4415.
Magnier-Watanabe R. M., & Senoo D. (2008). Organization characteristics as prescriptive factors of knowledge management initiatives. Journal of Knowledge Management, 12(1), 36-21.
Maier, R., & Remus, U. (2003). Implementing process-oriented knowledge management strategies. Journal of Knowledge Management, 7(4), 62–74.
Martensson, M. (2000). A critical review of knowledge management as a management tool. Journal of Knowledge Management, 4(3), 204–216.
Pham, Q. T., & Hara, Y. (2009). Combination of two KM Strategies by web 2.0. Knowledge Science Engineering and Management, 5914, 334-322.
Saaty, T.L. (1998).The analytic hierarchy process. University of Pittsburgh.
Sarvary M. (1999). Knowledge management and competition in the consulting industry. California Management Review, 41(2), 95–107.
Shafer, G. (1976). A mathematical theory of evidence. Princeton: Princeton University Press.
Spender, J. C ., & Grant, R.M. (1996). Knowledge and the firm: overview, Strategic Management Journal 17, 5–9.
Sung, T. K., & Gibson, D. V., (2005). Knowledge and technology transfer grid: empirical assessment. International Journal of Technology Management, 29(3/4), , 216–230.
Takeuchi, H., & Nonaka, I. (1995). The knowledge-creating company. New York, Oxford Univ. Press.
Valls, A., & Torra, V. (2000). Using classification as an aggregation tool in MCDM. Fuzzy Sets Syst*em,* 115(1), 159–168.
Wang Y. M., Yang J. B., Xu D. L. & Chin, K. S. (2009). Consumer preference prediction by using a hybrid evidential reasoning and belief rule-based methodology. Expert Systems with Applications, 36, 8421–8430.
Wu, W. W. (2008). Choosing knowledge management strategies by using a combined ANP and DEMATEL approach. Expert Systems with Applications, 35, 828–835.
Wu, W. W., & Lee, Y. T. (2007). Selecting knowledge management strategies by using the analytic network process. Expert Systems with Applications, 32, 841–847.
Yang, J. (2010). The knowledge management strategy and its effect on firm performance: A contingency analysis. International Journal Production Economics, 125, 215–223.
Yang, J. B. (2001). Rule and utility based evidential reasoning approach for multiattribute decision analysis under uncertainties. European Journal of Operational Research, 131, 31–61.
Yang, J. B., & Singh, M. G. (1994). An evidential reasoning approach for multiple attribute decision making with uncertainty. IEEE Transactions on Systems, Man, and Cybernetics, 24 (1), 1–18.
Yang, J. B., & Xu, D. L. (2002). Nonlinear information aggregation via evidential reasoning in multiattribute decision analysis under uncertainty, IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, 32 (3), 1–18.

Yang, J. B., & Xu, D. L. (2002). On the evidential reasoning algorithm for multiattribute decision analysis under uncertainty. IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans, 32(3), 1–17.

Yip M. W., Lau H. C., & Songip A. R. (2010). Influence of soft elements on knowledge management implementation in Malaysia higher learning institutions. Journal of Knowledge Management Practice, 11(3).

Zack, M. H. (1999). Developing a knowledge strategy. California Management Review, 41(3), 125–45.

Zhang, Y., Deng, X., Wei, D. & Deng, Y. (2012). Assessment of E-Commerce security using AHP and evidential reasoning. Expert Systems with Applications, 39, 3611–3623.