



# A hybrid fuzzy real option analysis and group ordinal approach for knowledge management strategy assessment

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## Abstract

The intensity of global competition and ever-increasing economic uncertainties has led organizations to search for more efficient and effective ways to improve organizational productivity by investing in knowledge management (KM) initiatives. In this research, we propose a framework to assess KM investment opportunities. Precise and crisp information is fundamentally indispensable in strategic investment assessment. However, the information concerning future investment opportunities in the real world is often imprecise or ambiguous. Initially, fuzzy real option valuation is used to estimate the value of the KM strategies. Next, a multi-criteria decision-making model is proposed to determine the optimal KM strategy in deferral time. Then, a group ordinal approach is used to capture and quantify the underlying uncertainties in the valuating process. Finally, the optimal KM strategy and the best time to implement this strategy is determined by a novel objective decision-making model. The contribution of this paper is fourfold: (1) it addresses the gaps in KM literature on the effective and efficient assessment of KM investment opportunities; (2) it provides a comprehensive and systematic framework that combines real option analysis with a group ordinal approach to assess KM investment strategies; (3) it considers fuzzy logic and fuzzy sets to represent ambiguous, uncertain or imprecise information; and (4) it uses a real-world case study to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms.

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## Introduction

Knowledge management (KM) strategies are high-level strategies that provide the organization with the knowledge and capabilities necessary for achieving its goals. KM strategies outline the necessary processes for managing knowledge effectively in organizations (Shaw & Edwards, 2005). The effective management of knowledge is recognized as a vehicle through which organizations can address their need for innovation and improved business performance (Kamara *et al.*, 2002). The effective management starts with a proper strategy (Gopal & Gagnon, 1995). In order to ensure the successful implementation of KM, it is imperative to properly evaluate and select an optimal KM strategy. Although the concept of KM strategy is receiving increased attention, the literature primarily relies on case studies, anecdotes and conceptual frameworks (Choi & Jong, 2010) and most KM

initiatives have been viewed primarily as information systems projects (Zack, 1999).

As knowledge is taking on an important strategic role, numerous companies are expecting their KM to be performed effectively in order to leverage and transform the knowledge into competitive advantages (Desouza, 2003; Liao, 2003; Zack, 1999). According to Kamara *et al.* (2002), KM is the organizational optimization of knowledge to achieve enhanced performance through the use of various methods and techniques. Also, KM is a systematic 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 this research, we propose a novel approach to assess KM investment opportunities. Initially, fuzzy real option valuation is used to estimate the value of the KM strategies. Next, a multi-criteria decision-making (MCDM) model is proposed to determine the optimal KM strategy in deferral time. Then, group ordinal approach is used to capture and quantify the underlying uncertainties in the valuating process. Finally, the optimal KM strategy and the best time to implement this strategy is determined by a novel objective decision-making model.

This paper is organized into seven sections. The next section provides a review of the current methods for the assessment of KM investment strategies. The subsequent section presents the mathematical notations and definitions used in our model and the fourth section illustrates the details of the proposed framework. Then, a real-world case study is used to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms. The paper will conclude with a discussion and implications in the penultimate section and conclusions and future research directions in the last section.

### A review of current methods for the assessment of KM investment strategies

Traditionally, the following valuation methods have been widely used to assess KM investment strategies: the net present value (Kaplan & Atkinson, 1998; Higson & Briginshaw, 2000), return on investment (Kumar, 2002), cost benefit analysis (Schniederjans *et al.*, 2004), information economics (Parker & Benson, 1989; Bakos & Kemerer, 1992) and return on management (Strassmann, 1997; Stix & Reiner, 2004; Chen *et al.*, 2006). Unfortunately, most traditional evaluation methods fail to: (1) incorporate the value of future opportunities and risks; (2) integrate objective data with subjective judgments; and (3) consider imprecise or ambiguous data inherent in real-world problems.

The net present value methods compare the present value of all future cash flows against the initial investment. However, the timing of the cash flows can distort

the evaluation of an investment and firm performance. Furthermore, the investment-level net present value tends to focus on precise quantitative results and not on imprecise qualitative considerations. This can result in eliminating major innovations because the benefits from new KM investment strategies are invisible and would not be captured by the traditional methods (Kaplan & Atkinson, 1998) and eventually, these technological breakthroughs do not pass the net present value test (Hayes & Abernathy, 1980).

The return on investment methods are commonly accepted in many organizations as the standard for capital investment evaluation and selection (Farbey *et al.*, 1993). However, these methods are designed to measure the objective and monetary impacts of capital investments and are unable to capture many intangible costs or qualitative benefits that KM brings to the organization (Luehrman, 1997; Brealey & Myers, 1998). In addition, the return on investment methods are likely to underestimate the true profitability of a new KM investment strategy and overestimate the profitability for the old ones because they employ the book value for assets and inflated values for revenues (Kumar, 2002).

The cost benefit analysis methods overcome the problem of return on investment by finding some replacement measure for intangible costs or benefits and expressing them in monetary terms. These methods attempt to deal with two problems: (1) the difficulty of quantifying the value of indirect benefits, and (2) the difficulty of identifying intangible benefits or costs (Schniederjans *et al.*, 2004). Although, cost benefit analysis is useful where the costs and benefits are intangible, the method requires the existence of broad agreement on the measures used to evaluate the intangibles.

The information economics methods are a variant of cost benefit analysis tailored to cope with the intangible factors and uncertainties found in KM investment strategies (Parker & Benson, 1989). However, the decision-making process used in these methods is based on a ranking and scoring technique of intangibles and risks factors associated with the KM investment strategy. The strength of the information economics methods is that they focus on simple and idealized settings often requiring many simplifying assumptions (Bakos & Kemerer, 1992).

The return on management methods argue that KM serves primarily to help managers do their job. These methods use the concept of value-added productivity and the ratio of 'output/input' as an approach to identify the impact of KM on business unit performance (Strassmann, 1997). The advantage of the return on management methods is that they concentrate on the contributions of KM to the management process and the disadvantage is the difficulty in defining the output of management (Stix & Reiner, 2004; Chen *et al.*, 2006).

In addition to the above traditional methods, there is a stream of research studies which emphasizes real option

analysis (ROA). The ROA differs from the traditional methods in terms of the priceability of the underlying investment project (McGrath, 1997). With the traditional methods, the underlying investment project of an option is priced as known (Black & Scholes, 1973) whereas in KM investment situations the price of an underlying investment project is rarely known (McGrath, 1997). The ROA uses three basic types of data: (1) current and possible future investment options, (2) the desired capabilities sought by the organization, and (3) the relative risks and costs of other available KM investment options.

The real options are commonly valued with the Black-Scholes option pricing formula (Black & Scholes, 1973, 1974), the binomial option valuation method (Cox *et al.*, 1979) and Monte-Carlo methods (Boyle, 1977). These methods assume that the underlying markets can be imitated accurately as a process. Although this assumption may hold for some quite efficiently traded financial securities, it may not hold for real investments that do not have existing markets (Collan *et al.*, 2009). Recently, a simple novel approach to ROA called the Datar-Mathews method (Datar & Mathews, 2004, 2007; Mathews & Salmon, 2007) was proposed where the real option value is calculated from a pay-off distribution, derived from a probability distribution of the NPV for an investment project generated with a Monte-Carlo simulation. This approach does suffer from the market process assumptions associated with the Black-Scholes method (Black & Scholes, 1974).

When valuating an investment opportunity using ROA, it is required to estimate several parameters (i.e. expected payoffs and costs or investment deferral time). However, the estimation of uncertain parameters in the KM investment valuation process is often very challenging. Most traditional methods use probability theory in their treatment of uncertainty. Fuzzy logic and fuzzy sets can represent ambiguous, uncertain or imprecise information in ROA by formalizing inaccuracy in human decision-making (Collan *et al.*, 2009). For example, fuzzy sets allow for graduation of belonging in future cash-flow estimation (i.e. future cash flow is about 5000 dollars in the third year). Fuzzy set algebra developed by Zadeh (1965) is the formal body of theory that allows the treatment of imprecise estimates in uncertain environments.

In recent years, several researchers have combined fuzzy sets theory with ROA. Carlsson & Fullér (2003) introduced a real option heuristic in a fuzzy environment, where the present values of expected cash flows and expected costs were estimated by trapezoidal fuzzy numbers. Chen *et al.* (2007) developed a comprehensive methodology for evaluating information technology investment in a nuclear power plant based on ROA and fuzzy risk analysis. Frode (2007) used the conceptual real option framework of Dixit & Pindyck (1994) to estimate the value of investment opportunities in the Norwegian hydropower industry. Villani (2008) combined ROA with

game theory to value the investment opportunities and the value of flexibility as a real option while analysing the competition with game theory. Collan *et al.* (2009) presented a new fuzzy ROA method that considered the dynamic nature of the profitability assessment. As cash flows taking place in the future come closer, information changes, and uncertainty is reduced. Chrysafis & Papadopoulos (2009) used statistical data to present an application of a new method of constructing fuzzy estimators for the parameters of a given probability distribution function. Wang & Hwang (2007) applied fuzzy set theory to model uncertain and flexible project information. They used a fuzzy compound-options model to evaluate the value of each project because traditional project valuation methods often underestimate the risky project.

Although several studies have focused on the successful evaluation and implementation of KM strategies, few of those have provided analytical methods to systematically evaluate KM investment opportunities. Wiig *et al.* (1997) argue that carrying out KM effectively requires support from a repertoire of methods, techniques and tools. Wu *et al.* (2008) have used ROA to provide a framework for the evaluation of knowledge-based organizations under uncertainty. Fan *et al.* (2009) proposed a fuzzy linguistic framework for evaluating KMC which included two parts: one was an evaluation hierarchy with attributes and the other was a judgment matrix model with two dimensions. Tseng *et al.* (2010) used an analytical network process in a framework to address the interdependence relations of criteria in KM strategies. They also used fuzzy sets to interpret the linguistic information in accordance with a subjective perception environment. Wu & Lee (2007) argued that the KM strategy selection is a multiple criteria decision-making problem with a large number of complex factors as multiple evaluation criteria. They developed a framework based on the analytic network process to help companies evaluate and select KM strategies. Wu (2008) later enhanced the earlier model proposed by Wu & Lee (2007) and proposed a solution based on a combined analytic network process and the decision-making trial and evaluation laboratory approach to evaluate and select KM strategies.

### **Mathematical notations and definitions**

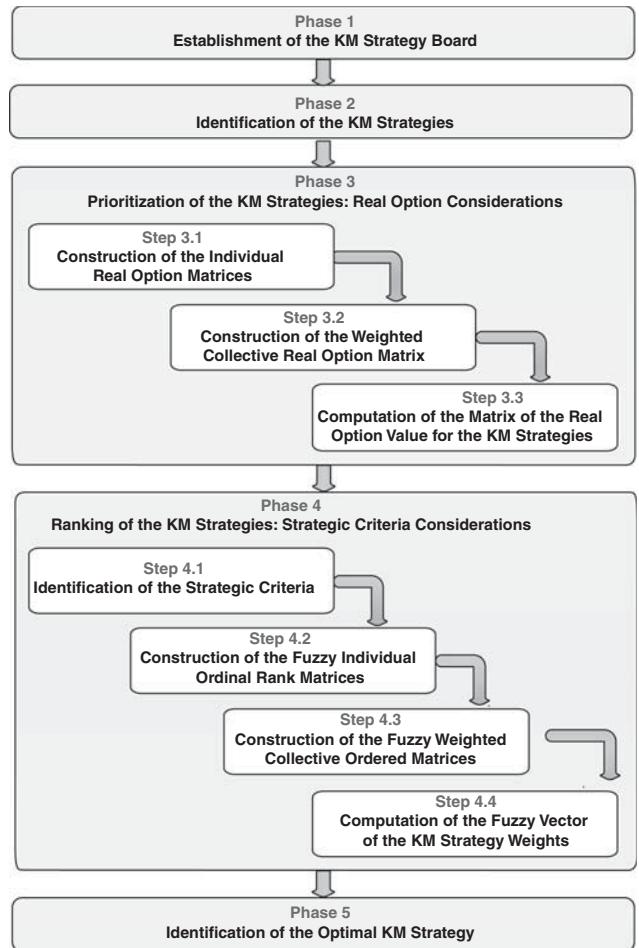
Let us introduce the following mathematical notations and definitions:

$\tilde{S}_i(t_j)$	The weighted collective fuzzy present value of the expected payoffs of the $i$ th KM strategy at time $t_j$
$\tilde{X}_i(t_j)$	The weighted collective fuzzy present value of the expected cost of the $i$ th KM strategy at time $t_j$
$\tilde{S}_i^k(t_j)$	The individual fuzzy present value of the expected payoffs of the $i$ th KM strategy at time $t_j$ evaluated by the KM strategy board member ( $KMSB_k$ )

$\tilde{X}_i^k(t_j)$	The individual fuzzy present value of the expected cost of the $i^{\text{th}}$ KM strategy at time $t_j$ evaluated by the KM strategy board member ( $KMSB_k$ )
$E(\tilde{S}_i(t_j))$	The possibilistic mean value of the weighted collective present value of expected payoffs of the $i^{\text{th}}$ KM strategy at time $t_j$
$E(\tilde{X}_i(t_j))$	The possibilistic mean value of the weighted collective expected costs of the $i^{\text{th}}$ KM strategy at time $t_j$
$(\sigma^2(t_j))_i$	The variance of the weighted collective fuzzy present value of expected payoffs of the $i^{\text{th}}$ KM strategy at time $t_j$ evaluated by the KM strategy board member ( $KMSB_k$ )
$\delta_i$	The value loss over the duration of the option
$r_i$	The risk-free interest rate
$N(d_{1i}(t_j))$	The KM strategy $i^{\text{th}}$ cumulative normal probability distribution for the $d_1$
$N(d_{2i}(t_j))$	The KM strategy $i^{\text{th}}$ cumulative normal probability distribution for the $d_2$
$t_h$	The maximum deferral time of the KM strategies
$t_1$	The minimum deferral time of the KM strategies
$\tilde{r}_{ij}$	The fuzzy ordinal rank of the $i^{\text{th}}$ KM strategy with respect to the $j^{\text{th}}$ strategic criterion
$\tilde{r}_{ij}^k$	The fuzzy ordinal rank of the $i^{\text{th}}$ KM strategy with respect to the $j^{\text{th}}$ strategic criterion evaluated by the KM strategy board member ( $KMSB_k$ )
$R_i^k(\tilde{r}_{ij}^k)$	The assigned score to $\tilde{r}_{ij}^k$ by the KM strategy board member ( $KMSB_k$ )
$R_i(\tilde{r}_{ij}^k)$	The assigned collective score to $\tilde{r}_{ij}^k$
$bs_{ij}(R_i(\tilde{r}_{ij}^k))$	The Borda score for $R_i(\tilde{r}_{ij}^k)$
$w_j$	The importance weight of the $j^{\text{th}}$ strategic criterion
$c_j$	The $j^{\text{th}}$ strategic criterion
$A_i$	The $i^{\text{th}}$ KM strategy
$p$	The number of the KM strategy strategic criteria
$m$	The number of the KM strategy board members
$n$	The number of alternative KM strategies
$frov_i(t_j)$	The fuzzy real option value of the $i^{\text{th}}$ KM strategy at time $t_j$
$f_{V_i}$	The fuzzy weight of the $i^{\text{th}}$ KM strategy
$D_{frov}$	The fuzzy real option value matrix of the KM strategies
$FV$	The fuzzy weight vector of the KM strategies
$\underline{w}(KMSB)_k$	The voting power of the KM strategy board member ( $KMSB_k$ ) for scoring ( $k = 1, 2, \dots, m$ )

### The proposed framework

The framework depicted in Figure 1 is proposed to assess the alternative KM strategies. The framework consists of several steps modularized into five phases:



**Figure 1** The proposed framework for selecting the optimal KM strategy.

#### Phase 1: establishment of the KM strategy board

In the first phase, a KM strategy board is established. Let us assume that  $m$  KM strategy board members are selected to participate in the evaluation process.

$$\underline{KMSB} = [(KMSB)_1, (KMSB)_2, \dots, (KMSB)_k, \dots, (KMSB)_m]$$

#### Phase 2: identification of the KM strategies

In this phase, the KM strategy board identifies the alternative KM strategies. Let us assume that this board has identified  $n$  alternative KM strategies with the maximum deferral time of  $t_h$ .

$$\underline{A} = [A_1, A_2, \dots, A_i, \dots, A_n].$$

#### Phase 3: prioritization of the KM strategies: real option considerations

In this phase, the Dos Santos (1994) real option equations are used to prioritize the KM strategies. This phase is divided into the following three steps.

### Step 3.1: Construction of the individual real option matrices

The following individual real option matrices are given by each KM strategy board member:

$$\tilde{D}_{ro}^k = \begin{bmatrix} \tilde{S}(t_1) & \tilde{S}(t_2) & \dots & \tilde{S}(t_h) & \tilde{X}(t_1) & \tilde{X}(t_2) & \dots & \tilde{X}(t_h) \\ A_1 & \begin{bmatrix} \tilde{S}_1^k(t_1) & \tilde{S}_1^k(t_2) & \dots & \tilde{S}_1^k(t_h) & \tilde{X}_1^k(t_1) & \tilde{X}_1^k(t_2) & \dots & \tilde{X}_1^k(t_h) \end{bmatrix} \\ A_2 & \begin{bmatrix} \tilde{S}_2^k(t_1) & \tilde{S}_2^k(t_2) & \dots & \tilde{S}_2^k(t_h) & \tilde{X}_2^k(t_1) & \tilde{X}_2^k(t_2) & \dots & \tilde{X}_2^k(t_h) \end{bmatrix} \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \dots & \vdots \\ A_n & \begin{bmatrix} \tilde{S}_n^k(t_1) & \tilde{S}_n^k(t_2) & \dots & \tilde{S}_n^k(t_h) & \tilde{X}_n^k(t_1) & \tilde{X}_n^k(t_2) & \dots & \tilde{X}_n^k(t_h) \end{bmatrix} \end{bmatrix} \quad (1)$$

(for  $k = 1, 2, \dots, m$ )

The following trapezoidal fuzzy numbers can be used for the individual fuzzy present values of the expected payoffs and cost of the  $i$ th KM strategy at time  $t_j$  by the KM strategy board member ( $KMSB_k$ ):

$$\begin{aligned} \tilde{S}_i^k(t_j) &= ((S_i^k(t_j))^a, (S_i^k(t_j))^b, (S_i^k(t_j))^\alpha, (S_i^k(t_j))^\beta) \\ \tilde{X}_i^k(t_j) &= ((X_i^k(t_j))^a, (X_i^k(t_j))^b, (X_i^k(t_j))^\alpha, (X_i^k(t_j))^\beta) \end{aligned} \quad (2)$$

(for  $j = 1, 2, \dots, h$ ).

The following intervals are used:

- $((S_i^k(t_j))^a, (S_i^k(t_j))^b)$ : The most possible values of the expected payoffs of the  $i$ th KM strategy at time  $t_j$  evaluated by KM strategy board member ( $KMSB_k$ )
- $((S_i^k(t_j))^a + (S_i^k(t_j))^\beta)$ : The upward potential for the expected payoffs of the  $i$ th KM strategy at time  $t_j$  evaluated by KM strategy board member ( $KMSB_k$ )
- $((S_i^k(t_j))^\alpha - (S_i^k(t_j))^\beta)$ : The downward potential for the expected payoffs of the  $i$ th KM strategy at time  $t_j$  evaluated by the KM strategy board member ( $KMSB_k$ )
- $((X_i^k(t_j))^a, (X_i^k(t_j))^b)$ : The most possible values of the expected cost of the  $i$ th KM strategy at time  $t_j$  evaluated by the KM strategy board member ( $KMSB_k$ )
- $((X_i^k(t_j))^a + (X_i^k(t_j))^\beta)$ : The upward potential for the expected cost of the  $i$ th KM strategy at time  $t_j$  evaluated by the KM strategy board member ( $KMSB_k$ )
- $((X_i^k(t_j))^\alpha - (X_i^k(t_j))^\beta)$ : The downward potential for the expected cost of the  $i$ th KM strategy at time  $t_j$  evaluated by the KM strategy board member ( $KMSB_k$ )

Consequently, substituting Eq. (2) into matrix (1), the individual real option matrices can be rewritten as:

$$\tilde{D}_{ro}^k(t_j) = \begin{bmatrix} \tilde{S}(t_j) & \tilde{X}(t_j) \\ A_1 & \begin{bmatrix} ((S_1^k(t_j))^a, (S_1^k(t_j))^b, (S_1^k(t_j))^\alpha, (S_1^k(t_j))^\beta) & ((X_1^k(t_j))^a, (X_1^k(t_j))^b, (X_1^k(t_j))^\alpha, (X_1^k(t_j))^\beta) \\ A_2 & \begin{bmatrix} ((S_2^k(t_j))^a, (S_2^k(t_j))^b, (S_2^k(t_j))^\alpha, (S_2^k(t_j))^\beta) & ((X_2^k(t_j))^a, (X_2^k(t_j))^b, (X_2^k(t_j))^\alpha, (X_2^k(t_j))^\beta) \\ \vdots & \vdots & \vdots \\ A_n & \begin{bmatrix} ((S_n^k(t_j))^a, (S_n^k(t_j))^b, (S_n^k(t_j))^\alpha, (S_n^k(t_j))^\beta) & ((X_n^k(t_j))^a, (X_n^k(t_j))^b, (X_n^k(t_j))^\alpha, (X_n^k(t_j))^\beta) \end{bmatrix} \end{bmatrix} \end{bmatrix} \quad (3)$$

### Step 3.2: Construction of the weighted collective real option matrix

This framework allows for assigning different voting power weights to each KM strategy board member:

$$\underline{W}(KMSB) = [w(KMSB)_1, w(KMSB)_2, \dots, w(KMSB)_j, \dots, w(KMSB)_m]. \quad (4)$$

Therefore, in order to form a fuzzy weighted collective real option matrix, the individual fuzzy real option matrices will be aggregated by the voting powers as follows:

$$\tilde{D}_{ro}(t_j) = \begin{bmatrix} \tilde{S}(t_j) & \tilde{X}(t_j) \\ A_1 & \begin{bmatrix} \tilde{S}_1(t_j) & \tilde{X}_1(t_j) \end{bmatrix} \\ A_2 & \begin{bmatrix} \tilde{S}_2(t_j) & \tilde{X}_2(t_j) \end{bmatrix} \\ \vdots & \vdots \\ A_n & \begin{bmatrix} \tilde{S}_n(t_j) & \tilde{X}_n(t_j) \end{bmatrix} \end{bmatrix}, \quad (5)$$

where

$$\tilde{S}_i(t_j) = \frac{\sum_{k=1}^m (w(KMSB)_k) (\tilde{S}_i^k(t_j))}{\sum_{k=1}^m w(KMSB)_k}, \quad (6)$$

$$\tilde{X}_i(t_j) = \frac{\sum_{k=1}^m (w(KMSB)_k) (\tilde{X}_i^k(t_j))}{\sum_{k=1}^m w(KMSB)_k}, \quad (7)$$

### Step 3.3: Computation of the matrix of the real option value for the KM strategies

The real options values of the KM strategies at times  $t_1, t_2, \dots, t_h$  can be determined by the following fuzzy real option value matrix:

$$\tilde{D}_{frov} = \begin{bmatrix} t_1 & t_2 & \dots & t_h \\ A_1 & \begin{bmatrix} frov_1(t_1) & frov_1(t_2) & \dots & frov_1(t_m) \end{bmatrix} \\ A_2 & \begin{bmatrix} frov_2(t_1) & frov_2(t_2) & \dots & frov_2(t_m) \end{bmatrix} \\ \vdots & \vdots & \ddots & \vdots \\ A_n & \begin{bmatrix} frov_n(t_1) & frov_n(t_2) & \dots & frov_n(t_m) \end{bmatrix} \end{bmatrix} \quad (8)$$

or

$$\tilde{D}_{frov}(t_j) = \begin{bmatrix} A_1 & \left[ \tilde{S}_1(t_j) \cdot e^{-\delta t_j} \cdot N(d_{11}(t_j)) - \tilde{X}_1(t_j) \cdot e^{-rt_j} \cdot N(d_{21}(t_j)) \right] \\ A_2 & \left[ \tilde{S}_2(t_j) \cdot e^{-\delta t_j} \cdot N(d_{12}(t_j)) - \tilde{X}_2(t_j) \cdot e^{-rt_j} \cdot N(d_{22}(t_j)) \right] \\ \vdots & \vdots \\ A_n & \left[ \tilde{S}_n(t_j) \cdot e^{-\delta t_j} \cdot N(d_{1n}(t_j)) - \tilde{X}_n(t_j) \cdot e^{-rt_j} \cdot N(d_{2n}(t_j)) \right] \end{bmatrix} \\ = \begin{bmatrix} frov_1(t_j) \\ frov_2(t_j) \\ \vdots \\ frov_n(t_j) \end{bmatrix}, \quad (9)$$

where the KM strategy  $i^{\text{th}}$  cumulative normal probability distribution for  $d_1$  and  $d_2$  are as follows:

$$D_1(t_j) = \begin{bmatrix} N(d_1(t_j)) & N(d_2(t_j)) \\ A_1 & \left[ N(d_{11}(t_j)) \quad N(d_{21}(t_j)) \right] \\ A_2 & \left[ N(d_{12}(t_j)) \quad N(d_{22}(t_j)) \right] \\ \vdots & \vdots \\ A_n & \left[ N(d_{1n}(t_j)) \quad N(d_{2n}(t_j)) \right] \end{bmatrix}, \quad (10)$$

$$D_2(t_j) = \begin{bmatrix} d_1(t_j) & d_2(t_j) \\ A_1 & \left[ d_{11}(t_j) \quad d_{21}(t_j) \right] \\ A_2 & \left[ d_{12}(t_j) \quad d_{22}(t_j) \right] \\ \vdots & \vdots \\ A_n & \left[ d_{1n}(t_j) \quad d_{2n}(t_j) \right] \end{bmatrix} \quad (11)$$

or equivalently:

$$D_2(t_j) = \begin{bmatrix} d_1(t_j) & d_2(t_j) \\ A_1 & \left[ \frac{Ln\left(\frac{E(\tilde{S}_1(t_j))}{E(\tilde{X}_1(t_j))}\right) + (r_1 - \delta_1 + \sigma_1^2(t_j)/2) \cdot t_j}{\sigma_1(t_j) \sqrt{t_j}} \quad \frac{Ln\left(\frac{E(\tilde{S}_1(t_j))}{E(\tilde{X}_1(t_j))}\right) + (r_1 - \delta_1 + \sigma_1^2(t_j)/2) \cdot t_j}{\sigma_1^2(t_j) \sqrt{t_j}} \right] \\ A_2 & \left[ \frac{Ln\left(\frac{E(\tilde{S}_2(t_j))}{E(\tilde{X}_2(t_j))}\right) + (r_2 - \delta_2 + \sigma_2^2(t_j)/2) \cdot t_j}{\sigma_2(t_j) \sqrt{t_j}} \quad \frac{Ln\left(\frac{E(\tilde{S}_2(t_j))}{E(\tilde{X}_2(t_j))}\right) + (r_2 - \delta_2 + \sigma_2^2(t_j)/2) \cdot t_j}{\sigma_2^2(t_j) \sqrt{t_j}} \right] \\ \vdots & \vdots \\ A_n & \left[ \frac{Ln\left(\frac{E(\tilde{S}_n(t_j))}{E(\tilde{X}_n(t_j))}\right) + (r_n - \delta_n + \sigma_n^2(t_j)/2) \cdot t_j}{\sigma_n(t_j) \sqrt{t_j}} \quad \frac{Ln\left(\frac{E(\tilde{S}_n(t_j))}{E(\tilde{X}_n(t_j))}\right) + (r_n - \delta_n + \sigma_n^2(t_j)/2) \cdot t_j}{\sigma_n^2(t_j) \sqrt{t_j}} \right] \end{bmatrix}, \quad (12)$$

where  $E$  and  $\sigma^2$  denote the probabilistic mean value and probabilistic variance operators as follows:

$$D_3(t_j) = \begin{bmatrix} E(\tilde{X}(t_j)) & E(\tilde{X}(t_j)) & \sigma^2(t_j) \\ A_1 & \left[ E(\tilde{S}_1(t_j)) \quad E(\tilde{X}_1(t_j)) \quad \sigma_1^2(t_j) \right] \\ A_2 & \left[ E(\tilde{S}_2(t_j)) \quad E(\tilde{X}_2(t_j)) \quad \sigma_2^2(t_j) \right] \\ \vdots & \vdots & \vdots \\ A_n & \left[ E(\tilde{S}_n(t_j)) \quad E(\tilde{X}_n(t_j)) \quad \sigma_n^2(t_j) \right] \end{bmatrix}. \quad (13)$$

Since  $\tilde{S}_i$  and  $\tilde{X}_i$  are trapezoidal fuzzy numbers, the formulas proposed by Carlsson *et al.* (2007) are used to find their expected value and the variance:

$$E(S_i(t_j)) = \frac{(S(t_j))^a + (S(t_j))^b}{2} + \frac{(S(t_j))^\beta - (S(t_j))^\alpha}{6},$$

$$E(\tilde{X}_i(t_j)) = \frac{(X(t_j))^a + (X(t_j))^b}{2} + \frac{(X(t_j))^\beta - (X(t_j))^\alpha}{6},$$

$$\sigma_i^2(t_j) = \frac{((S(t_j))^b - (S(t_j))^a)^2}{4} + \frac{((S(t_j))^\beta - (S(t_j))^\alpha)((S(t_j))^\alpha + (S(t_j))^\beta)}{6} + \frac{((S(t_j))^\alpha + (S(t_j))^\beta)^2}{24} \quad (14)$$

#### Phase 4: ranking of the KM strategies: strategic criteria considerations

In the real-life problems, the evaluation of the KM strategies involves uncertainties. Therefore, in this phase, the group ordinal approach is utilized to determine the importance of the KM strategies with regard to the strategic criteria of investment risks and a chain of other criteria. This phase is divided into the following four steps.

##### Step 4.1: Identification of the strategic criteria

In this step, the KM strategy board will determine a list of the strategic criteria. Let us consider  $c_1, c_2, \dots, c_p$  as the strategic criteria.

**Step 4.2: Construction of the fuzzy individual ordinal rank matrices**

The fuzzy individual rank matrix of the KM strategies evaluated by the KM strategy board member ( $KMSB_k$ ) are as follows:

$$(\tilde{A})^k = \begin{bmatrix} c_1 & & & & c_p \\ A_1 & \left( (r_{11}^k)^a, (r_{11}^k)^b, (r_{11}^k)^\alpha, (r_{11}^k)^\beta \right) & \left( (r_{12}^k)^a, (r_{12}^k)^b, (r_{12}^k)^\alpha, (r_{12}^k)^\beta \right) & \cdots & \left( (r_{1p}^k)^a, (r_{1p}^k)^b, (r_{1p}^k)^\alpha, (r_{1p}^k)^\beta \right) \\ A_2 & \left( (r_{21}^k)^a, (r_{21}^k)^b, (r_{21}^k)^\alpha, (r_{21}^k)^\beta \right) & \left( (r_{22}^k)^a, (r_{22}^k)^b, (r_{22}^k)^\alpha, (r_{22}^k)^\beta \right) & \cdots & \left( (r_{2p}^k)^a, (r_{2p}^k)^b, (r_{2p}^k)^\alpha, (r_{2p}^k)^\beta \right) \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ A_n & \left( (r_{n1}^k)^a, (r_{n1}^k)^b, (r_{n1}^k)^\alpha, (r_{n1}^k)^\beta \right) & \left( (r_{n2}^k)^a, (r_{n2}^k)^b, (r_{n2}^k)^\alpha, (r_{n2}^k)^\beta \right) & \cdots & \left( (r_{np}^k)^a, (r_{np}^k)^b, (r_{np}^k)^\alpha, (r_{np}^k)^\beta \right) \end{bmatrix} \quad (15)$$

or

$$(\tilde{A})^k = \begin{bmatrix} c_1 & c_2 & \cdots & c_p \\ A_1 & \tilde{r}_{11}^k & \tilde{r}_{12}^k & \cdots & \tilde{r}_{1p}^k \\ A_2 & \tilde{r}_{21}^k & \tilde{r}_{22}^k & \cdots & \tilde{r}_{2p}^k \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ A_n & \tilde{r}_{n1}^k & \tilde{r}_{n2}^k & \cdots & \tilde{r}_{np}^k \end{bmatrix}. \quad (16)$$

**Step 4.3: Construction of the fuzzy weighted collective ordered matrices**

Borda's score is then determined for each KM strategy with respect to  $P$  strategic criteria as follows:

$$BS(\tilde{R}) = \begin{bmatrix} c_1 & c_2 & \cdots & c_p \\ A_1 & bs_{ij} [R_1(\tilde{r}_{11}^k)] & bs_{ij} [R_1(\tilde{r}_{12}^k)] & \cdots & bs_{ij} [R_1(\tilde{r}_{1p}^k)] \\ A_2 & bs_{ij} [R_2(\tilde{r}_{21}^k)] & bs_{ij} [R_2(\tilde{r}_{22}^k)] & \cdots & bs_{ij} [R_2(\tilde{r}_{2p}^k)] \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ A_n & bs_{ij} [R_n(\tilde{r}_{n1}^k)] & bs_{ij} [R_n(\tilde{r}_{n2}^k)] & \cdots & bs_{ij} [R_n(\tilde{r}_{np}^k)] \end{bmatrix} \quad (19)$$

or

$$BS(\tilde{R}) = \begin{bmatrix} c_1 & c_2 & \cdots & c_p \\ A_1 & bs_{ij} [R_1^1((r_{11})^a, (r_{11})^b, (r_{11})^\alpha, (r_{11})^\beta)] & bs_{ij} [R_1^2((r_{12})^a, (r_{12})^b, (r_{12})^\alpha, (r_{12})^\beta)] & \cdots & bs_{ij} [R_1^l((r_{1p})^a, (r_{1p})^b, (r_{1p})^\alpha, (r_{1p})^\beta)] \\ A_2 & bs_{ij} [R_2^1((r_{21})^a, (r_{21})^b, (r_{21})^\alpha, (r_{21})^\beta)] & bs_{ij} [R_2^2((r_{22})^a, (r_{22})^b, (r_{22})^\alpha, (r_{22})^\beta)] & \cdots & bs_{ij} [R_2^l((r_{2p})^a, (r_{2p})^b, (r_{2p})^\alpha, (r_{2p})^\beta)] \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ A_n & bs_{ij} [R_n^1((r_{n1})^a, (r_{n1})^b, (r_{n1})^\alpha, (r_{n1})^\beta)] & bs_{ij} [R_n^2((r_{n2})^a, (r_{n2})^b, (r_{n2})^\alpha, (r_{n2})^\beta)] & \cdots & bs_{ij} [R_n^l((r_{np})^a, (r_{np})^b, (r_{np})^\alpha, (r_{np})^\beta)] \end{bmatrix}, \quad (20)$$

Consequently, for each strategic criterion  $c_j$  of KM strategies, the following matrix is considered:

$$\tilde{A}_j = \begin{bmatrix} \tilde{r}_{1j}^1 & \tilde{r}_{1j}^2 & \cdots & \tilde{r}_{1j}^m \\ \tilde{r}_{2j}^1 & \tilde{r}_{2j}^2 & \cdots & \tilde{r}_{2j}^m \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{r}_{nj}^1 & \tilde{r}_{nj}^2 & \cdots & \tilde{r}_{nj}^m \end{bmatrix}. \quad (17)$$

Now, for each strategic criterion of preference ordering of the KM strategies, scores of  $n-1, n-2, \dots, 1, 0$  to the first ranked, second ranked ... last ranked are assigned. That is:

$$\tilde{R}_j = \begin{bmatrix} R_1^1(\tilde{r}_{1j}^1) & R_1^2(\tilde{r}_{1j}^2) & \cdots & R_1^m(\tilde{r}_{1j}^m) \\ R_2^1(\tilde{r}_{2j}^1) & R_2^2(\tilde{r}_{2j}^2) & \cdots & R_2^m(\tilde{r}_{2j}^m) \\ \vdots & \vdots & \cdots & \vdots \\ R_n^1(\tilde{r}_{nj}^1) & R_n^2(\tilde{r}_{nj}^2) & \cdots & R_n^m(\tilde{r}_{nj}^m) \end{bmatrix}. \quad (18)$$

where

$$R_i(\tilde{r}_{ij}^k) = \frac{\sum_{k=1}^m (w(KMSB)_k) [R_i^k(\tilde{r}_{ij}^k)]}{\sum_{k=1}^m w(KMSB)_k}. \quad (21)$$

**Step 4.4: Computation of the fuzzy vector of the KM strategy weights**

The fuzzy weights vector of the KM strategies is calculated for matrix (19) based on the Borda score as follows:

$$FV = [fv_1 \ fv_2 \ \cdots \ fv_n]', \quad (22)$$

where

$$fv_i = \frac{\sum_{j=1}^p (w_j) [bs_{ij} [R_i(\tilde{r}_{ij}^k)]]}{\sum_{j=1}^p w_j}. \quad (23)$$

**Table 1 Three alternative KM strategies<sup>a</sup>**

KM strategies	Description
System-oriented style (Strategy 1)	This style puts more emphasis on codifying and reusing knowledge
Human-oriented style (Strategy 2)	This style is on acquiring and sharing tacit knowledge and interpersonal experience
Dynamic style (Strategy 3)	This style emphasizes both explicit and tacit methods

<sup>a</sup> Source: Choi & Lee (2003).

### Phase 5: identification of the optimal KM strategy

Next, the following multi-objective decision-making model is used with a series of constraints to aggregate the values of the KM strategies and the importance weights of the KM strategies obtained in phases (2) and (3).

$$\begin{aligned} \text{Max } Z_1 = & \frac{E[frov_1(t_1)]}{E[frov_1(t_1)] + \dots + E[frov_n(t_1)]} \cdot x_{11} \\ & + \frac{E[frov_1(t_2)]}{E[frov_1(t_2)] + \dots + E[frov_n(t_2)]} \cdot x_{12}, \\ & + \dots \\ & \frac{E[frov_n](t_m)}{E[frov_1(t_m)] + \dots + E[frov_n(t_m)]} \cdot x_{nm} \end{aligned}$$

(Model P)

$$\begin{aligned} \text{Max } Z_2 = & \frac{E(fv_1)}{[E(fv_1) + \dots + E(fv_n)]} \cdot (x_{11} + x_{12} + \dots + x_{1m}) \\ & + \frac{E(fv_2)}{[E(fv_1) + \dots + E(fv_n)]} \cdot (x_{21} + x_{22} + \dots + x_{2m}) \\ & + \dots \frac{E(fv_n)}{[E(fv_1) + \dots + E(fv_n)]} \cdot (x_{n1} + x_{n2} + \dots + x_{nm}) \end{aligned}$$

subject to:

$$f_1(x_{11}, x_{12}, \dots, x_{nm}) \leq 0$$

$$f_2(x_{11}, x_{12}, \dots, x_{nm}) \leq 0$$

⋮

$$f_r(x_{11}, x_{12}, \dots, x_{nm}) \leq 0$$

$$\gamma_1 + \gamma_2 + \dots + \gamma_n \leq 1$$

$$\gamma_1 = x_{11} + x_{12} + \dots + x_{1m}$$

$$\gamma_2 = x_{21} + x_{22} + \dots + x_{2m}$$

⋮

$$\gamma_n = x_{n1} + x_{n2} + \dots + x_{nm}$$

$$x_{ij} = 0, 1 \quad (i = 1, 2, \dots, n), \quad (j = 1, 2, \dots, m)$$

where  $f_i(x_1, x_2, \dots, x_n)$  is a given function of the  $n$  KM strategies.

The optimal solution for model (P) is the best KM strategy at the time  $t_j$ . Next, we present a numerical example to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures and algorithms.

**Table 2 The normalized mean value of the fuzzy real options for the three KM strategies**

Deferral time	KM Strategy 1	KM Strategy 2	KM Strategy 3
0	0.39	0.27	0.32
1	0.31	0.32	0.29
2	0.26	0.39	0.35

### Case study

The model presented in section 'Mathematical notations and definitions' was used to help Semicon Technologies,<sup>1</sup> a large manufacturer of semiconductor equipment, memory chips, microprocessors and microcontrollers located in Jersey City select an optimal KM strategy for their technical support division.

### Phase 1

In this phase, the management team established a committee of four KM strategy board members which included:

(KMSB)<sub>1</sub>: Customer Service Manager

(KMSB)<sub>2</sub>: Technical Support Manager

(KMSB)<sub>3</sub>: Research & Development Manager

(KMSB)<sub>4</sub>: Capital Budgeting Manager

### Phase 2

In this phase, the committee agreed to use three styles of KM strategies suggested by Choi & Lee (2003) in the evaluation process. A listing of the three KM styles considered by the Semicon management is presented in Table 1.

Choi & Lee (2003) found that KM methods can be categorized into four styles: dynamic, system-oriented, human-oriented and passive. They showed that the emphasis of the dynamic style is on knowledge reusability and knowledge sharing and it results in higher performance. On the other hand, human- and system-oriented styles did not show any difference in terms of corporate performance and the passive style was very ineffective. The committee agreed passive style was not a feasible option.

<sup>1</sup>Some of the names and data presented in this study are changed to protect the anonymity of the company.

### Phase 3

The committee agreed to assign the following voting powers for the four KM strategy board members:  $W(KMSB) = (0.3, 0.2, 0.3, 0.2)$ . Next, Eqs. (1)–(14) were used to compute the matrix of the real option normalized value for the KM strategies in years 0, 1 and 2 presented in Table 2.

### Phase 4

In Step 4.1, the KM strategy board determined the following six strategic criteria for ranking the KM



**Figure 2** Six strategic criteria associated with selecting the optimal KM strategy.

strategies based on the group ordinal approach (Figure 2):

In step 4.2, Eqs. (15)–(18) were used to construct four fuzzy individual ordinal rank matrices (one for each committee member) given in Tables 3–6.

In step 4.3, with regard to the importance weight vector  $(w_1, w_2, w_3, w_4, w_5, w_6) = (0.15, 0.22, 0.23, 0.24, 0.21, 0.15)$ , Eqs. (19)–(21) were used to construct the fuzzy weighted collective ordered matrix given in Table 7.

In Step 4.4, Eqs. (22) and (23) were used to compute the fuzzy vector of the KM strategy weights provided in Table 8.

### Phase 5

In this phase, the following proposed two-objective decision-making model was used to determine the optimal KM strategy:

$$\begin{aligned} \text{Max } Z_1 = & 0.39x_{10} + 0.31x_{11} + 0.26x_{12} \\ & + 0.27x_{20} + 0.32x_{21} + 0.39x_{22} \\ & + 0.32x_{30} + 0.29x_{31} + 0.35x_{32} \end{aligned}$$

(Model P)

$$\begin{aligned} \text{Max } Z_2 = & 0.28(x_{10} + x_{11} + x_{12}) \\ & + 0.32(x_{20} + x_{21} + x_{22}) \\ & + 0.4(x_{30} + x_{31} + x_{32}) \end{aligned}$$

subject to:

$$\begin{aligned} y_1 + y_2 + \cdots + y_n & \leq 1 \\ y_1 & = x_{10} + x_{11} + x_{12} \\ y_2 & = x_{20} + x_{21} + x_{22} \\ y_3 & = x_{30} + x_{31} + x_{32} \\ x_{10}, x_{11}, x_{12}, x_{20}, x_{21}, x_{22}, x_{30}, x_{31}, x_{32} & = 0, 1 \end{aligned}$$

**Table 3** The fuzzy individual ordinal rank matrix evaluated by the customer service manager

KM strategies	Firm-specific risks	Development risks	Environment risks	Communication and knowledge sharing	Culture and people	Creativity
Strategy 1	(1.75, 2.25, 0.25, 0.25)	(1.75, 2.25, 0.25, 0.25)	(1.75, 2.25, 0.25, 0.25)	(0.75, 1.25, 0.25, 0.25)	(0.75, 1.25, 0.25, 0.25)	(1.75, 2.25, 0.25, 0.25)
Strategy 2	(2.75, 3.25, 0.25, 0.25)	(2.75, 3.25, 0.25, 0.25)	(2.75, 3.25, 0.25, 0.25)	(1.75, 2.25, 0.25, 0.25)	(1.75, 2.25, 0.25, 0.25)	(2.75, 3.25, 0.25, 0.25)
Strategy 3	(0.75, 1.25, 0.25, 0.25)	(0.75, 1.25, 0.25, 0.25)	(0.75, 1.25, 0.25, 0.25)	(2.75, 3.25, 0.25, 0.25)	(2.75, 3.25, 0.25, 0.25)	(0.75, 1.25, 0.25, 0.25)

**Table 4** The fuzzy individual ordinal rank matrix evaluated by the technical support manager

KM strategies	Firm-specific risks	Development risks	Environment risks	Communication and knowledge sharing	Culture and people	Creativity
Strategy 1	(2.6, 3.4, 0.1, 0.1)	(0.6, 1.4, 0.1, 0.1)	(1.6, 2.4, 0.1, 0.1)	(0.6, 1.4, 0.1, 0.1)	(0.6, 1.4, 0.1, 0.1)	(2.6, 3.4, 0.1, 0.1)
Strategy 2	(1.6, 2.4, 0.1, 0.1)	(2.6, 3.4, 0.1, 0.1)	(2.6, 3.4, 0.1, 0.1)	(1.6, 2.4, 0.1, 0.1)	(1.6, 2.4, 0.1, 0.1)	(1.6, 2.4, 0.1, 0.1)
Strategy 3	(0.6, 1.4, 0.1, 0.1)	(1.6, 2.4, 0.1, 0.1)	(0.6, 1.4, 0.1, 0.1)	(2.6, 3.4, 0.1, 0.1)	(2.6, 3.4, 0.1, 0.1)	(0.6, 1.4, 0.1, 0.1)

**Table 5 The fuzzy individual ordinal rank matrix evaluated by the research & development manager**

KM strategies	Firm-specific risks	Development risks	Environment risks	Communication and knowledge sharing	Culture and people	Creativity
Strategy 1	(1.9,2.1,0.1,0.1)	(1.9,2.1,0.1,0.1)	(2.9,3.1,0.1,0.1)	(0.9,1.1,0.1,0.1)	(1.9,2.1,0.1,0.1)	(1.9,2.1,0.1,0.1)
Strategy 2	(2.9,3.1,0.1,0.1)	(2.9,3.1,0.1,0.1)	(1.9,2.1,0.1,0.1)	(2.9,3.1,0.1,0.1)	(0.9,1.1,0.1,0.1)	(2.9,3.1,0.1,0.1)
Strategy 3	(0.9,1.1,0.1,0.1)	(0.9,1.1,0.1,0.1)	(0.9,1.1,0.1,0.1)	(1.9,2.1,0.1,0.1)	(2.9,3.1,0.1,0.1)	(0.9,1.1,0.1,0.1)

**Table 6 The fuzzy individual ordinal rank matrix evaluated by the capital budgeting manager**

KM strategies	Firm-specific risks	Development risks	Environment risks	Communication and knowledge sharing	Culture and people	Creativity
Strategy 1	(1.75,2.25,0.25,0.25)	(1.75,2.25,0.25,0.25)	(1.75,2.25,0.25,0.25)	(0.75,1.25,0.25,0.25)	(0.75,1.25,0.25,0.25)	(1.75,2.25,0.25,0.25)
Strategy 2	(2.75,3.25,0.25,0.25)	(2.75,3.25,0.25,0.25)	(2.75,3.25,0.25,0.25)	(1.75,2.25,0.25,0.25)	(1.75,2.25,0.25,0.25)	(2.75,3.25,0.25,0.25)
Strategy 3	(0.75,1.25,0.25,0.25)	(0.75,1.25,0.25,0.25)	(0.75,1.25,0.25,0.25)	(2.75,3.25,0.25,0.25)	(2.75,3.25,0.25,0.25)	(0.75,1.25,0.25,0.25)

**Table 7 The fuzzy weighted collective ordered matrix**

KM strategies	Firm-specific risks	Development risks	Environment risks	Communication and knowledge sharing	Culture and people	Creativity
Strategy 1	(1.957,2.435,0.175,0.175)	(1.052,2.035,0.175,0.175)	(2.065,2.535,0.175,0.175)	(0.765,1.235,0.175,0.175)	(1.065,1.535,0.175,0.175)	(1.965,2.225,0.175,0.175)
Strategy 2	(2.565,2.995,0.175,0.175)	(2.765,3.235,0.175,0.175)	(3.625,4.12,0.175,0.175)	(1.425,2.536,0.175,0.175)	(1.465,1.935,0.175,0.175)	(2.565,3.035,0.175,0.175)
Strategy 3	(0.765,1.235,0.175,0.175)	(0.965,0.435,0.175,0.175)	(0.765,1.235,0.175,0.175)	(2.565,2.935,0.175,0.175)	(2.765,3.335,0.175,0.175)	(0.765,1.235,0.175,0.175)

**Table 8 The fuzzy weights vector of the three KM strategies**

The fuzzy weights vector	KM Strategy 1	KM Strategy 2	KM Strategy 3
FV	(1.705,2.090,0.175,0.175)	(2.861,3.496,0.175,0.175)	(1.814,2.154,0.175,0.175)

The results from model (P) identified the human-oriented style (KM strategy 2) with an implementation in the second year as the optimal strategy. These findings were communicated to the Semicon management who proceeded with the implementation of the results.

### Discussion and implications

It is hard to say for sure what KM strategy is the best, but, the selection process could be made more comprehensive and systematic. The group MCDM process used at Semicon Technologies was intended to enhance decision-making and promote consensus. The four committee members were highly educated; three of them held graduate degrees and one of them held a doctorate. To this end, a more logical and persuasive MCDM method was necessary to gain their confidence and support. Although the committee members were educated and creative, their managerial judgment and intuition was limited by background and experience. One manager lacked strategic management skills while another had

limited experience in the semiconductor industry. Upon completion of the KM selection process, a meeting was held with the committee to discuss the results and finalize the recommendations. The four committee members unanimously agreed that the proposed framework provided invaluable analysis aids and information processing support. They were convinced that the result was unbiased and consistent.

Armed with this feedback, the committee members were confident that they could sell their recommendation to the top management. Nevertheless, the committee was aware that the transformation of Semicon into a knowledge-centric organization is a gradual process and cannot be achieved overnight. The committee members knew that building internal alliances and establishing KM as an activity that cuts across different functional areas was a difficult task. They agreed to target various groups and key people at Semicon in order to gain their support. The committee members began building internal alliances with functional units and focused their efforts on getting other line managers on board. This

process involved fostering collaboration and avoiding alienation of potential internal allies. The committee also decided to get the line managers on board. Gaining the line management support resulted in the dedication of some line budget to the implementation process. This led to a virtuous circle since the fact that some line managers agreed to pay for some of the KM implementation expenses increased their commitment. This encouraged other line managers to jump on the bandwagon and participate in the KM implementation initiatives.

The internal alliance building process would not be complete without top management support. The committee was adamant about the importance of gaining support from the top management. Gaining the top management support was easier than it may seem from the outside. The committee members had already built internal alliances and support of various key people and line managers. They discussed the overwhelming internal support and the tangible and intangible benefits of the selected strategy with the top management who in turn agreed to implement the proposed recommendation. The committee was also required to develop a long-term plan to measure the KM success through qualitative measures (i.e., user feedback, system usage and customer feedback) and quantitative measures (i.e., return on investment, gains in market share and quality improvement).

The analysis of this case study allows the articulation of a series of key factors that can be considered as important in contributing to the successful selection and implementation of KM strategies. The first is building internal alliances. The second element is getting the line managers on board. The third factor is the full and continual support given by top management. The fourth key ingredient is the persistent and systematic processes in place to measure the KM success.

### **Conclusions and future research directions**

KM has been the subject of much discussion over the past decade. When organizations begin a KM initiative, one of the first and most important decisions that the organizations will need to make is choosing the right and optimal KM strategy. In this research, we proposed a framework to assess KM investment opportunities. We used fuzzy real option valuation to estimate the value of the KM strategies because the information concerning future investment opportunities in the real world is often imprecise or ambiguous. Next, we used a MCDM model

to determine the optimal KM strategy in deferral time. Then, the group ordinal approach was used to capture and quantify the underlying uncertainties in the evaluation process. Finally, the optimal KM strategy and the best time to implement this strategy was determined by a novel objective decision-making model. This framework can be easily generalized to N-dimensional problems.

We have developed a framework that can be used to evaluate KM investment projects based on the real option concept. This approach incorporates the linkage among economic value, real option value and KM investments that could lead to a better-structured decision process. The overall contributions of the novel framework proposed in this study are threefold:

- (a) our framework addresses the gaps in the KM literature on the effective and efficient assessment of KM investment opportunities,
- (b) our framework provides a comprehensive and systematic framework that combines ROA with a group ordinal approach to assess KM investment strategies, and
- (c) current KM assessment models are somewhat limited in their ability to come to grips with issues of inference and fuzziness. The proposed framework considers fuzzy logic and fuzzy sets to represent ambiguous, uncertain or imprecise information in the KM strategic evaluation process.

Future research considering correlation coefficients between the risk and benefit factors is rather challenging but necessary to gain insight into this interaction influence in the application of ROA to KM investment decisions. Another possible future research direction is to investigate other drivers that influence the KM investment selection process. For example, Lee *et al.* (2005) describe a metric for assessing the performance based on the components that increase a company's economic value by creating, accumulating and utilizing knowledge. These value drivers could also be incorporated into the model proposed in this study. Future studies can utilize the proposed model in other knowledge intensive industries planning to assess KM investment projects and initiatives.

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