A fuzzy logic model for benchmarking the knowledge management performance of construction firms

Serdar Kale and Erkan A. Karaman

Abstract: Knowledge management is rapidly becoming a key organizational capability for creating competitive advantage in the construction industry. The emergence of knowledge management in this capacity poses enormous challenges to executives of construction firms. This paper proposes a model for benchmarking the knowledge management performance of construction firms that can guide and assist construction business executives in meeting these challenges. The proposed model incorporates benchmarking and knowledge management concepts with fuzzy set theory to adequately handle imprecision, vagueness, and uncertainty that prevail in this process. It uses the fuzzy-weighted average (FWA) algorithm to evaluate the knowledge management performance of construction firms. It is an internal reporting model that can provide powerful diagnostic information to executives of construction firms by evaluating their firm's knowledge management performance, identifying their firm's strengths and weaknesses with regard to each knowledge management practice, and setting priorities for managerial actions related to knowledge management practices that need improvement. A real-world case study is presented to illustrate the implementation and utility of the proposed model.

Key words: knowledge management, fuzzy logic, performance evaluation, benchmarking, and construction firm.

Résumé : La gestion des connaissances devient rapidement une capacité organisationnelle clé pour créer un avantage compétitif dans l'industrie de la construction. L'émergence de la gestion des connaissances dans ce sens présente d'énormes défis aux directeurs des compagnies de construction. Le présent article propose un modèle d'analyse comparative du rendement des compagnies de construction en gestion des connaissances, analyse qui peut guider et aider les directeurs des compagnies de construction à relever ces défis. Le modèle proposé incorpore les concepts d'analyse comparative et de gestion des connaissances et la théorie des ensembles flous afin de traiter de manière adéquate de l'imprécision et de l'incertitude inhérentes à ce processus. Il utilise l'algorithme de moyenne pondérée floue (FWA) pour évaluer le rendement des compagnies de construction en gestion des connaissances. Il s'agit d'un modèle de communication de l'information de gestion qui peut fournir des renseignements diagnostiques puissants aux directeurs des compagnies de construction en évaluant le rendement de gestion des connaissances de leur compagnie, en identifiant les forces et les faiblesses de leur compagnie quant à la pratique de gestion des connaissances et en établissant des priorités pour les actions de gestion reliées aux pratiques de gestion des connaissances ayant besoin d'amélioration. Une étude de cas dans le monde réel est présentée pour illustrer l'implantation et l'utilité du modèle proposé.

Mots-clés : gestion des connaissances, logique floue, évaluation du rendement, analyse comparative, compagnie de construction.

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Introduction

It is increasingly recognized that knowledge management is a key capability for construction firms in today's business environment (e.g., Kululanga and McCaffer 2001; Egbu 2004; Yu et al. 2009). Indeed, developing models to evaluate and improve this key capability within construction firms has emerged as a topical issue in the construction management literature. The most notable models include the Knowledge Management Measurement model (Kululanga and McCaffer 2001); Cross-sectoral Learning in the Virtual Enterprise (CLEVER) (Kamara et al. 2002); Improving Management Performance through Knowledge Transformation (IMPaKT) (Robinson et al. 2004); Startup-Takeoff-Expansion-Progressive-Sustainability (STEPS) (Robinson et al. 2005); Knowledge Value Adding Model (KVAM) (Yu et al. 2009); and Measuring Knowledge Retention (Arif et al. 2009). These models have provided important insight into the concept of knowledge management and how it can be measured and used for improvement in construction firms.

The paper presented herein presents a simple model for evaluating the knowledge management performance of construction firms. The proposed model is a synthesis of bench-

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S. Kale. Izmir Institute of Technology, Department of Architecture, Urla - 35430, Izmir, Turkey.
E.A. Karaman. Balikesir University, Department of Civil Engineering, Cagis - 10145, Balikesir, Turkey.

Corresponding author: Serdar Kale (e-mail: serdarkale@iyte.edu.tr).

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marking (Camp 1989), knowledge management models (e.g., Gold et al. 2001; Lindsey 2002) and fuzzy set theory (e.g., Zadeh 1965; Kao and Liu 2001). It differs from previously proposed models in three ways. First, benchmarking has been suggested as a popular performance measurement approach in the construction management literature (e.g., Sommerville and Robertson 2000; Fang et al. 2004; Lam et al. 2004; Luu et al. 2008). Yet it has not been used to evaluate the knowledge management performance of construction firms. Second, the competitive environment in which construction firms operate was almost ignored in performance measurement models (e.g., Kululanga and McCaffer 2001; Arif et al. 2009) developed to evaluate the knowledge management practices of construction firms. This exclusion is one of the major limitations of performance evaluation models of knowledge management practices in construction firms. Including the competitive environment in evaluating knowledge management presents important benefits such as the ability to identify, understand, and adopt best practices and the opportunity to establish standards against which knowledge management practices can be compared and consequently improved (Chen et al. 2009). Developing a performance measurement model that incorporates the competitive environment, therefore, is a highly topical and essential research issue for construction firms. Third, the proposed performance measurement models (e.g., Kululanga and McCaffer 2001; Yu et al. 2009) predominantly use linguistic variables to evaluate the knowledge management performance of construction firms. A linguistic variable is one whose values are not numbers, but rather words or sentences presented in either a natural or artificial language. Yet linguistic variables usually have meanings that are imprecise, vague, or not mathematically operable. They do not, therefore, constitute a well-defined boundary. The fuzzy set theory (Zadeh 1965) is a powerful tool that deals effectively with uncertain, imprecise, and vague linguistic variables. Fuzzy set theory uses a language with syntax and semantics to translate linguistic variables into numerical reasoning. It is thus a convenient and flexible tool to deal with the ambiguity, uncertainty, and vagueness that prevails in measuring knowledge management performance of construction firms.

The main objectives of the proposed framework are (1) to assist executives of construction firms to identify basic components of knowledge management, (2) to provide a foundation on which systems and processes for effective knowledge management practices can be built, and (3) to provide executives of construction firms an internal reporting tool to evaluate and benchmark their firm's knowledge management performance.

Benchmarking

Benchmarking is one of the most powerful performance modeling approaches. It provides a systematic framework for identifying, classifying, and evaluating firms' processes, activities and performances. The primary objective of benchmarking is continuous improvement through observing the activities of other firms (Camp 1989). Different types of benchmarking have been proposed in the literature. Spendolini (1992) classifies benchmarking into three major types: (1) *internal*, (2) *competitive*, and (3) *generic*. Internal benchmarking involves a firm's efforts to explore and analyze best practices within its departments and functions and to transplant uncovered best practices to other departments and functions. Competitive benchmarking involves a firm's efforts to analyze the best practices of its rivals and to imitate discovered best practices in its operations and activities. Generic benchmarking refers to a firm's efforts to explore the best practices of firms other than its rivals that are operating in the same industry or even firms operating in other industries. Competitive benchmarking has been one of the most commonly used benchmarking types in the literature. Competitive benchmarking is commonly carried out by completing a number of tasks. The basic tasks of competitive benchmarking include the following: (1) identifying what is to be benchmarked, (2) developing a benchmarking model, (3) selecting rival firm(s) to be used in benchmarking (i.e., comparative firms), (4) collecting data for benchmarking, (5) analyzing data for benchmarking, (6) diagnosing performance gap(s), and (7) presenting conclusions and recommendations regarding practices that need improvement (e.g., Camp 1989).

The following section addresses the first task of competitive benchmarking. It presents a succinct review of knowledge management literature.

Knowledge management

The concept of knowledge management has been centre stage in the construction management literature for more than a decade (e.g., Kululanga et al. 1998; Egbu 1999; Carrillo et al. 2000; Patel et al. 2000; Robinson et al. 2004; Fong and Kwok 2009). Knowledge management refers to the creation and subsequent management of an environment that encourages knowledge to be created, shared, learned, and organized for the benefit of the firm (Sarrafzadeh et al. 2006). The contemporary research studies on knowledge management (e.g., Lee and Choi 2003; Chuang 2004; Fong and Chu 2006; Fong and Kwok 2009) build on the social–technical perspective (i.e., a synthesis of the social and technical perspectives). The central goal of these research studies has been to identify the primary knowledge management practices, and those that have emerged include (1) *knowledge management process* and (2) *knowledge management enablers*.

Different models have been set forth to define the knowledge management process (e.g., Wiig 1993; Nonaka and Takeuchi 1994; Gold et al. 2001; Kululanga and McCaffer 2001). A succinct review of these models reveals that they vary in their scope and level of detail. The model proposed in this paper uses Gold et al.'s (2001) knowledge management process model because their model is sufficiently broad to permit a complete analysis of knowledge management processes and commonly used in knowledge management studies (Lin 2007). Gold et al.'s (2001) knowledge management process model involves four sub-processes: the acquisition, conversion, application, and protection of knowledge. The knowledge acquisition process involves searching for and finding entirely new knowledge or creating new knowledge out of existing knowledge. The knowledge conversion process involves the transfer of knowledge among social actors (i.e., groups and individuals). The knowledge application process involves the utilization of knowledge to improve the efficiency and effectiveness of activities and operations. The knowledge protection process involves securing knowledge from inappropriate and illegal use or theft.

Knowledge management enablers represents the organizational mechanisms, tools and techniques that stimulate creating and developing knowledge within an organization and also facilitate its sharing, diffusion, and protection (Lee and Choi 2003; Yeh et al. 2006). They provide a foundation on which effective knowledge management can be built. Chuang (2004) decomposes knowledge management enablers into three groups: (1) *technical knowledge management resource,* (2) *cultural knowledge management resource, and (3) structural knowledge management resource*.

Technical knowledge management resource includes a number of information and communication technologies (ICT) used by the firm to support and enhance the creation, storage and retrieval, transfer, application, sharing, and protection of organizational knowledge. Construction firms use several information and communication technologies to support their knowledge management processes. The most commonly used information and communication technologies in construction firms include (e.g., Carrillo 2004; Fong and Kwok 2009): intranets, content management systems, document management systems relational and object databases, groupware and workflow systems, data warehousing systems, and data mining systems.

Cultural knowledge management resource represents a firm's organizational culture. Organizational culture includes a set of values, norms, beliefs, expectations, and assumptions that is widely shared in an organization (Huber 2001). Drucker et al. (1996) consider organizational culture as the "corporate glue" that binds social actors to the goals and objectives of the organization. This corporate glue informally shapes the values, assumptions, beliefs, and behaviors of the social actors that can encourage or impede the creation, sharing, and diffusion of organizational knowledge. Cultural mechanisms for enhancing knowledge management activities in construction firms include: defining and communicating a clear organizational vision; attaching a high value to knowledge; emphasizing continuous improvement; empowering individuals by encouraging creativity, risk taking, questioning, and experimentation; having a high tolerance for mistakes; emphasizing openness, frequent contact, and effective communication; building trust to encourage sharing knowledge within the organization and with selected business partners; and valuing internal and external collaboration.

Structural knowledge management resource represents a firm's organizational structure. Organizational structure can be considered a social architecture of roles and flows of authority, work materials, information, and decision-making processes that make up an organization (Pennings 1992). It provides a social framework for the transformation of inputs into outputs. This social framework formally shapes the behaviors of social actors and acts as an information and knowledge filter that can limit what a social actor sees in its operating environment, and influence how a social actor perceives and interprets its environment. Structural mechanisms construction firms use to facilitate knowledge management activities include (e.g., Carrillo 2004; Fong and Kwok 2009): formal meetings, on-the-job training, and post-project reviews.

Previous research studies provide strong empirical support that a firm's knowledge management processes and knowledge management enablers positively influence its knowledge management performance (e.g., Gold et al. 2001; Lee and Choi 2003). Therefore, it is essential for construction firms to evaluate and benchmark their knowledge management processes and knowledge management enablers by developing or adopting a benchmarking model.

Thus far the concepts of benchmarking and knowledge management are defined. The following section presents the basic concepts of fuzzy set theory that will be used in developing a realistic model for benchmarking the knowledge management performance of construction firms.

Basic concepts of fuzzy set theory

A fuzzy set is one that assigns grades of membership between 0 and 1 to objects within its universe of discourse (Zadeh 1965). If X is a universal set whose elements are $\{x\}$, then a fuzzy set A is defined by its membership function A: X $\in$ [0,1] which assigns to every x a degree of membership A in the interval [0,1].

A fuzzy number, on the other hand, is a convex normalized fuzzy set of the real line R whose membership function is piecewise continuous. It is a special fuzzy set $A = \{(x, \mu_A(x)), x \in R\}$, where x takes its values on the real line, R: $-\alpha < x < +\alpha$ and $\mu_F(x)$ is a continuous mapping from R to the closed interval [1,0]. A fuzzy number can be represented by any shape but the most commonly used shape is a triangle. A triangular fuzzy number (TFN) is denoted by $A = (L, M, U)$ and has the following triangular membership function (Fig. 1):

$$[1] \qquad \mu_A(x) = \begin{Bmatrix} 0 & x < L \\ \dfrac{x-L}{M-L} & L \le x \le M \\ \dfrac{U-x}{U-M} & M \le x \le U \\ 0 & x > U \end{Bmatrix}$$

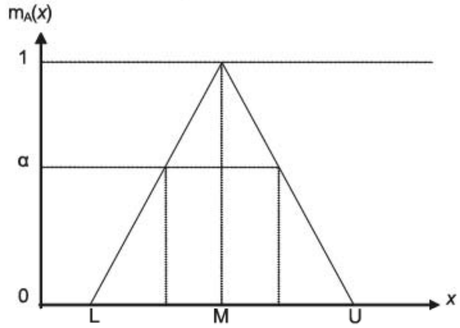
where M is the most possible value of fuzzy number A, L and U represent lower and upper bounds, respectively.

The α-cut of a fuzzy number $A^\alpha = \{x | \mu_A(x) \ge \alpha\}$ $\alpha \in \{0,1\}$, is expressed as $(l^\alpha, m^\alpha, u^\alpha)$. The confidence interval of A^α α-level can also be stated A^α $[L^{(\alpha)}, U^{(\alpha)}]$. The terms $L^{(\alpha)}$ and $U^{(\alpha)}$ represent lower and upper boundaries of confidence interval, respectively (Fig. 1).

Arithmetic operations on triangular fuzzy numbers

Fuzzy arithmetic operations are based on two properties of fuzzy numbers (Klir and Yuan 1995): (1) each fuzzy number can be fully and uniquely represented by its family of α-cuts and (2) α-cuts of each fuzzy number are closed intervals of real numbers for all α [0,1]. It is these properties that enable researchers to define arithmetic operations on fuzzy numbers in terms of arithmetic operations on their α-cuts. The basic arithmetic operations of two fuzzy triangular numbers $A = (L_1, M_1, U_1)$ and $B = (L_2, M_2, U_2)$ based on closed interval arithmetic are defined as follows (Klir and Yuan 1995):

Fig. 1. Triangular membership function and the α-cut of set for A.



$$[2a] \quad A^{\alpha} \oplus B^{\alpha} = [L_1^{(\alpha)} + L_2^{(\alpha)}, U_1^{(\alpha)} + U_2^{(\alpha)}]$$

$$[2b] \quad A^{\alpha} \ominus B^{\alpha} = [L_1^{(\alpha)} - U_2^{(\alpha)}, U_1^{(\alpha)} - L_2^{(\alpha)}]$$

$$[2c] \quad A^{\alpha} \otimes B^{\alpha} = [L_1^{(\alpha)} * L_2^{(\alpha)}, U_1^{(\alpha)} * U_2^{(\alpha)}]$$

$$[2d] \quad A^{\alpha} \oslash B^{\alpha} = [L_1^{(\alpha)} / U_2^{(\alpha)}, U_1^{(\alpha)} / L_2^{(\alpha)}]$$

where A^{α} and B^{α} represent the α-cuts of the fuzzy numbers A and B, respectively, and $\oplus$, $\ominus$, $\otimes$, and $\oslash$ denote addition, subtraction, multiplication, and division operators for two intervals of confidence, respectively.

Model development

The knowledge management benchmarking model proposed in this paper builds on the concepts that have been set forth by benchmarking models (e.g., Camp 1989; Spendolini 1992), knowledge management frameworks (e.g., Gold et al. 2001; Lindsey 2002), and fuzzy set theory (e.g., Zadeh 1965; Kao and Liu 2001). The model consists of a seven-step procedure for benchmarking the knowledge management performance of construction firms. These steps are as follows: *Step 1*, identifying evaluation criteria for measuring knowledge management performance; *Step 2*, constructing the hierarchical structure for the evaluation criteria; *Step 3*, determining the importance weights of the evaluation criteria; *Step 4*, rating the knowledge management processes and enablers; *Step 5*, computing fuzzy knowledge management performance (FKMP) of construction firms; *Step 6*, ranking fuzzy knowledge management performance of construction firms; and *Step 7*, diagnosing performance gaps and setting priorities for managerial action.

Step 1. Identifying the evaluation criteria for measuring the knowledge management performance

The first step in benchmarking the knowledge management performance of construction firms is developing a set of evaluation criteria (C_i). Several knowledge management frameworks (e.g., Gold et al. 2001; Lindsey 2002) have been published in the literature. A succinct review of these proposed frameworks reveals that the set of benchmarking criteria should include (1) *knowledge management enablers* (C_1) and (2) *knowledge management processes* (C_2).

Step 2. Constructing the hierarchical structure for the evaluation criteria

The second step is constructing a hierarchical structure for benchmarking the knowledge management performance of construction firms. The published knowledge management frameworks (e.g., Gold et al. 2001; Lindsey 2002) proposed a two-level hierarchical structure for measuring knowledge management performance (Fig. 2). *Level 1* decomposes a construction firm's knowledge management performance into two criteria C_i (i = 1, 2): *knowledge management enablers* (C_1) and *knowledge management processes* (C_2). *Level 2* includes a set of sub-criteria C_{ij} (j = 1, 2,…k) where k denotes the number of sub-criteria for measuring each main criterion (C_i). Knowledge management enablers (C_1) can be decomposed into three sub-criteria: technical knowledge management resource ($C_{1.1}$), structural knowledge management resource ($C_{1.2}$), and cultural knowledge management resource ($C_{1.3}$). Knowledge management processes (C_2) includes four sub-criteria: knowledge acquisition ($C_{2.1}$), knowledge conversion ($C_{2.2}$), knowledge application ($C_{2.3}$), and knowledge protection ($C_{2.4}$).

Step 3. Determining the importance weights of the evaluation criteria

The third step involves identifying the importance weight of each criterion. The most common approach used in determining the importance of each criterion is to judge its importance with linguistic variables (e.g., low importance, moderate importance, high importance). These linguistic variables can be represented appropriately by using fuzzy triangular numbers. Therefore, these linguistic terms are transformed into fuzzy triangular numbers. Let $w_{ij,m}$ be the fuzzy triangular numbers representing the linguistic importance of criterion ij assigned by an evaluator from firm m (m = 1, 2…,n). The fuzzy average importance weight of C_{ij} th evaluation criterion can be computed as follows:

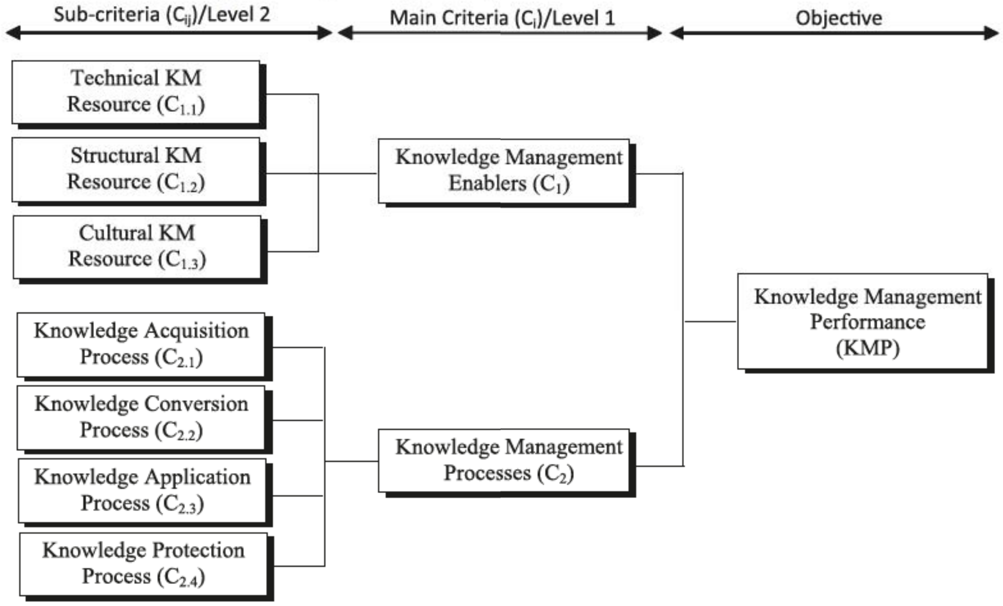
$$[3] \quad W_{ij} = \left(\frac{1}{n}\right) \otimes \sum_{m=1}^{n} w_{ij,m}$$

where $\otimes$ is the fuzzy multiplication operator, W_{ij} is the average fuzzy importance weight of criterion C_{ij}, and n is the number of firms that participated in benchmarking.

Step 4. Rating knowledge management processes and enablers

The fourth step is rating the knowledge management processes and enablers of construction firms. A construction firm's knowledge management processes and enablers can be evaluated by using a two-stage process: (1) developing a set of multi-item scales for measuring each sub-criterion (R_{ij}) and (2) rating the construction firm's achievements with regard to each item using linguistic variables. Using multi-item scales to measure each sub-criterion (R_{ij}) enhances the reliability of the rating process. The linguistic variables used for rating the construction firm's achievement on each item are then transformed into fuzzy triangular numbers. Let $r_{ij,h}$ be the triangular fuzzy number representing the hth item (h = 1,2,…,s) measuring the performance ratings of sub-criterion ij, and s is the number of items used in measuring each sub-criterion (R_{ij}). The fuzzy average performance rating of sub-criterion

Fig. 2. Hierarchic framework for measuring knowledge management performance.



of construction firm m ($R_{ij,m}$) can be derived by using the following equation:

$$[4] \qquad R_{ij,m} = \left(\frac{1}{s}\right) \otimes \sum_{h=1}^{s} r_{ij,h}$$

Step 5. Computing a firm's knowledge management performance

Knowledge management performance is a function of level 1 criteria (i.e., the main criteria) and level 2 criteria (i.e., the sub-criteria). Therefore, computing a firm's knowledge management performance requires the consolidation of the fuzzy weights and ratings of level 1 and level 2 criteria presented in Fig. 2. This consolidation process starts from the sub-criteria level (level 2) and proceeds to the main-criteria level (level 1). The consolidation of average fuzzy importance weights (W_{ij}) and of the average fuzzy performance ratings (R_{ij}) of level 2 criteria (C_{ij}) provides fuzzy-weighted average performance ratings (R_i) for level 1 criteria (C_i). Similarly, the consolidation of the average fuzzy importance weights (W_i) and of the fuzzy-weighted-average performance ratings (R_i) of level 1 criteria (C_i) provides the fuzzy knowledge management performance (FKMP) of a construction firm.

The fuzzy-weighted average (FWA) method is used to aggregate the average fuzzy importance weights and the average fuzzy performance ratings of level 1 and level 2. The FWA method for measuring the fuzzy knowledge management performance (FKMP_m) of construction firm m can be defined as:

$$[5] \qquad R_{i,m} = \left(\sum_{j=1}^{k} R_{ij,m} \otimes W_{ij}\right) \oslash \sum_{j=1}^{k} W_{ij}$$

$$[6] \qquad \mathrm{FKMP}_m = \left(\sum_{i=1}^{l} R_{i,m} \otimes \mathrm{W}_i\right) \oslash \sum_{i=1}^{l} W_i$$

The above formulation is difficult to solve because it contains fuzzy numbers and fuzzy arithmetic operations (i.e., addition, multiplication, and division). Fuzzy arithmetic operations on fuzzy numbers, particularly the division operation, are difficult to carry out. Different algorithms (e.g., Guh et al. 2001; Kao and Liu 2001) have been proposed to facilitate the fuzzy arithmetic operations and to compute the fuzzy weighted average presented in eqs. [5] and [6]. The knowledge management performance benchmarking model presented in this paper uses Kao and Liu's (2001) algorithm as it is the most efficient algorithm. This algorithm involves transforming the α-cut solution of a fuzzy-weighted average to a linear fractional program and solving it by linear programming techniques. Appendix A presents the algorithm proposed by Kao and Liu (2001).

Step 6. Ranking knowledge management performance of construction firms

The sixth step is the ranking of construction firms based on their fuzzy knowledge management performance (FKMP). FKMP is a fuzzy expression, and, therefore, a method for ranking fuzzy expressions is required to compare the knowledge management performances of the construction firms. Several methods (e.g., Chen 1985; Chen and Klein 1997) have been presented in the literature for ranking fuzzy expressions. The model presented in this paper uses Chen and Klein's (1997) ranking method. This method is based on the fuzzy subtraction operation of a referential rectangle H from a fuzzy number, and it uses α-cuts for performing fuzzy subtraction operations. The ranking method for computing crisp values of knowledge management performance can be defined as:

$$[7] \qquad I(\mathrm{FKMP}_m) = \frac{\sum_{i=0}^{q} \left[(\mathrm{FKMP}_m)_U^{\alpha_i} - c\right]}{\sum_{i=0}^{q} \left[(\mathrm{FKMP}_m)_U^{\alpha_i} - c\right] - \sum_{i=0}^{q} \left[(\mathrm{FKMP}_m)_L^{\alpha_i} - d\right]}, \quad q \to \infty$$

where $I(\text{FKMP}_m)$ is the ranking index representing the knowledge management performance of construction firm m, q is the number of α-cuts, and $c = \min_{i,m}\{(\text{FKMP}_m)_L^{\alpha_i}\}$ and $d = \max_{i,m}\{(\text{FKMP}_m)_L^{\alpha_i}\}$ are the left and right barriers of the referential rectangle H_{FKMP}, respectively. The ranking index $I(\text{FKMP}_m)$ ranges from 0 to 1 ($0 \leq I(\text{FKMP}_m) \leq 1$). The larger the ranking index, the higher the preference for knowledge management performance becomes.

Step 7. Determining performance gaps in knowledge management practices

The final step in the benchmarking process is to identify performance gaps in the knowledge management practices of the constructions firms. Performance gaps can be negative, positive, or neutral. A positive performance gap implies that the ranking index of the case firm is larger than its rivals' indices for a given knowledge management practice. A negative performance gap implies that the case firm's ranking index is smaller than its rivals' indices for that knowledge management practice. Finally, a neutral performance gap suggests that the ranking index of the case firm equals those of its rivals for that knowledge management practice. Performance gaps in knowledge management practices can be diagnosed on two hierarchical levels: the main criteria level (C_i) and the sub-criteria level (C_{ij}). Diagnosing performance gaps at the main criteria level requires transforming fuzzy expressions into crisp values. Fuzzy weighted average performance ratings at the main criteria level (R_i) can be transformed into crisp values by using the following formula:

$$[8]\quad I(R_{i,m}) = \frac{\sum_{i=0}^{q}\left[(R_{i,m})_U^{\alpha_i} - f\right]}{\sum_{i=0}^{q}\left[(R_{i,m})_U^{\alpha_i} - f\right] - \sum_{i=0}^{q}\left[(R_{i,m})_L^{\alpha_i} - g\right]}, q \rightarrow \infty$$

where $I(R_{i,m})$ is the ranking index that represents the fuzzy weighted average performance rating of the main criterion of construction firm m, and $g = \min_{i,m}\{(R_{i,m})_L^{\alpha_i}\}$ and $f = \max_{i,m}\{(R_{i,m})_U^{\alpha_i}\}$ are the left and right barriers of the referential rectangle H_{Ri}, respectively.

Similarly, diagnosing performance gaps at the sub-criteria level requires transforming fuzzy expressions into crisp values. The following formula can be used for this purpose:

$$[9]\quad I(P_{ij,m}) = \frac{\sum_{i=0}^{q}\left[(P_{ij,m})_U^{\alpha_i} - v\right]}{\sum_{i=0}^{q}\left[(P_{ij,m})_U^{\alpha_i} - v\right] - \sum_{i=0}^{q}\left[(P_{ij,m})_L^{\alpha_i} - t\right]}, q \rightarrow \infty$$

$$[10]\quad P_{ij,m} = R_{ij,m} \otimes W_{ij}$$

where $I(P_{ij,m})$ is the index that represents the weighted performance rating of sub-criterion C_{ij} of construction firm m, $P_{ij,m}$ is the weighted fuzzy performance rating of sub-criterion C_{ij} of construction firm m, and $v = \min_{i,m}\{(P_{ij,m})_L^{\alpha_i}\}$ and $t = \max_{i,m}\{(P_{ij,m})_U^{\alpha_i}\}$ are the left and right barriers of the referential rectangle H_{Pij}, respectively. The ranking index for weighted fuzzy performance of a sub-criterion can be used to set priorities for managerial actions to improve deficient knowledge management practices.

Implementation of the proposed model: a case study

The case study approach was used in this study to illustrate the use of the proposed model for benchmarking the knowledge management performance of construction firms. This approach was chosen because it has been used extensively in previous performance measurement modeling studies in the construction management domain (e.g., Kamara et al. 2002; Carrillo and Chinowsky 2006). It is well-known that success in a competitive benchmarking study significantly depends on selecting the benchmark firms (i.e., the firms to be used in benchmarking). Selecting the case firm and its benchmark firms were based on three criteria: (1) topical relevance (i.e., firms were selected because they are known to have a particular interest in the subject area); (2) feasibility and access (i.e., the firm's executives were willing for their firms to participate in the case study) (Kamara et al. 2002); and (3) ensuring confidentiality and anonymity (i.e., neither the case firm nor its benchmark firms know the identity of participating firms). A two-step procedure was followed in this process. In the first step, the case study construction firm (i.e., construction firm A) was asked to list its top 10 rivals. In the second step, the authors contacted executives of the listed rival construction firms and briefly described the objectives, scope, and stages of the competitive benchmarking study along with the potential benefits of participating. Eight rivals of the case firm declined to participate. The case study firm (construction firm A), therefore, was benchmarked against its two primary rivals: construction firms B and C (n = 3). Construction firm A is located in İstanbul, Turkey. It has more than 155 full-time employees. Its turnover was over \$135 million in 2009. It generally undertakes infrastructure and general building projects. Construction firm B and C are located in İstanbul, Turkey and have 250 and 180 full-time employees, respectively.

The participating constructions firms were asked to form an evaluation committee. Each evaluation committee was composed of three top executives, including the chief executive officer or vice president of each firm. A construction industry profile of the evaluation committee members reveals their experience ranges from a minimum of 7 years to a maximum of 17 years, with an average of 12 years. These individuals were considered to be the most knowledgeable persons regarding their firm's knowledge management practices. Three series of interviews were conducted with each of the evaluation committees. The first series of interviews were preliminary in nature and focused on the firm's knowledge management practices. The second series of interviews focused on revising a preliminary set of measurement items (i.e., indicators for measuring each criterion), which were taken from previous research studies on knowledge management practices (e.g., Gold et al. 2001; Lee and Choi 2003). The initial set of measurement items was modified based on participants' feedback and suggestions. The third series of interviews focused on developing linguistics variables and their corresponding membership functions to measure importance weights and performance ratings. The final series of interviews involved administering the evaluation form.

Table 1. Fuzzy average ratings and weights of main and sub-criteria.

	Construction firm			
	A	B (rival 1)	C (rival 2)	
Main criteria C_i	Fuzzy average ratings ($R_{i,\mathrm{A}}$)	Fuzzy average ratings ($R_{i,\mathrm{B}}$)	Fuzzy average ratings ($R_{i,\mathrm{C}}$)	Fuzzy average weights (W_i)
C_1	(0.3336,0.4997,0.6888)	(0.0985,0.2238,0.4232)	(0.5476,0.7554,0.9046)	(0.3667,0.5500,0.7333)
C_2	(0.2957,0.4930,0.7315)	(0.1909,0.3940,0.6317)	(0.3579,0.5426,0.7371)	(0.4667,0.6500,0.8333)
Sub criteria C_{ij}	($R_{ij,\mathrm{A}}$)	($R_{ij,\mathrm{B}}$)	($R_{ij,\mathrm{C}}$)	(W_{ij})
$C_{1.1}$	(0.4321,0.5823,0.7338)	(0.1182,0.2182,0.4091)	(0.4909,0.6818,0.8545)	(0.2333,0.4000,0.5667)
$C_{1.2}$	(0.3122,0.4704,0.6473)	(0.1273,0.2500,0.4455)	(0.5091,0.6818,0.8364)	(0.3000,0.5000,0.7000)
$C_{1.3}$	(0.3243,0.4734,0.6643)	(0.0833,0.2083,0.4000)	(0.6583,0.8500,0.9417)	(0.5333,0.7000,0.8667)
$C_{2.1}$	(0.3923,0.5712,0.7484)	(0.3250,0.5000,0.6750)	(0.3875,0.5750,0.7625)	(0.3333,0.5000,0.6667)
$C_{2.2}$	(0.3701,0.5112,0.7341)	(0.1300,0.2850,0.4600)	(0.3500,0.5300,0.7100)	(0.3667,0.5500,0.7333)
$C_{2.3}$	(0.3764,0.5332,0.7468)	(0.3300,0.5150,0.7000)	(0.3700,0.5450,0.7300)	(0.4000,0.6000,0.8000)
$C_{2.4}$	(0.0838,0.2000,0.3282)	(0.0625,0.1313,0.3250)	(0.3375,0.5000,0.6750)	(0.0667,0.2500,0.4333)

A knowledge management performance evaluation instrument (KMPE-I) was prepared based on a succinct review of previous research studies on knowledge management (e.g., Gold et al. 2001; Lee and Choi 2003) and interviews with the evaluation committees. KMPE-I consists of two parts. The first part of KMPE-I includes a series of questions that identify the importance of each criterion. In this part, evaluators were asked to rate the importance of each main criterion (C_i) and each sub-criterion (C_{ij}) using linguistic variables that ranged from "totally unimportant (TU)," "quite unimportant (QU)," "unimportant (U)," "barely important (BU)," "moderately important (MI)", "very important (VI)," to "extremely important (EI)."

The second part of KMPE-I included a set of items for evaluating construction firms' knowledge management enablers and processes. In the second part of the evaluation form, committee members were instructed to rate their satisfaction with their firm's achievement on each indicator using linguistic variables that ranged from "completely unsatisfied (CU)," "mostly unsatisfied (MU)," "somewhat unsatisfied (SU)," "somewhat satisfied (SS)," "mostly satisfied (MS)," to "completely satisfied (CS)."

Each evaluation committee's linguistic responses regarding the importance weight assigned to each criterion and the level of satisfaction with the achievement in each item were transformed into triangular fuzzy numbers. The triangular fuzzy numbers associated with the linguistic terms used to measure the relative importance of each criterion were set as TU = (0,0,0.2); QU = (0,0.2,0.4); U = (0.2,0.35,0.5); BU = (0.3,0.5,0.7); MI = (0.5,0.65,0.8); VI = (0.6,0.8,1); and EI = (0.8,1.0,1.0). Fuzzy average importance weight of each criterion was computed by using eq. [3]. Table 1 present the fuzzy average weights level 1 (W_i) and (W_{ij}) of level 2 criteria.

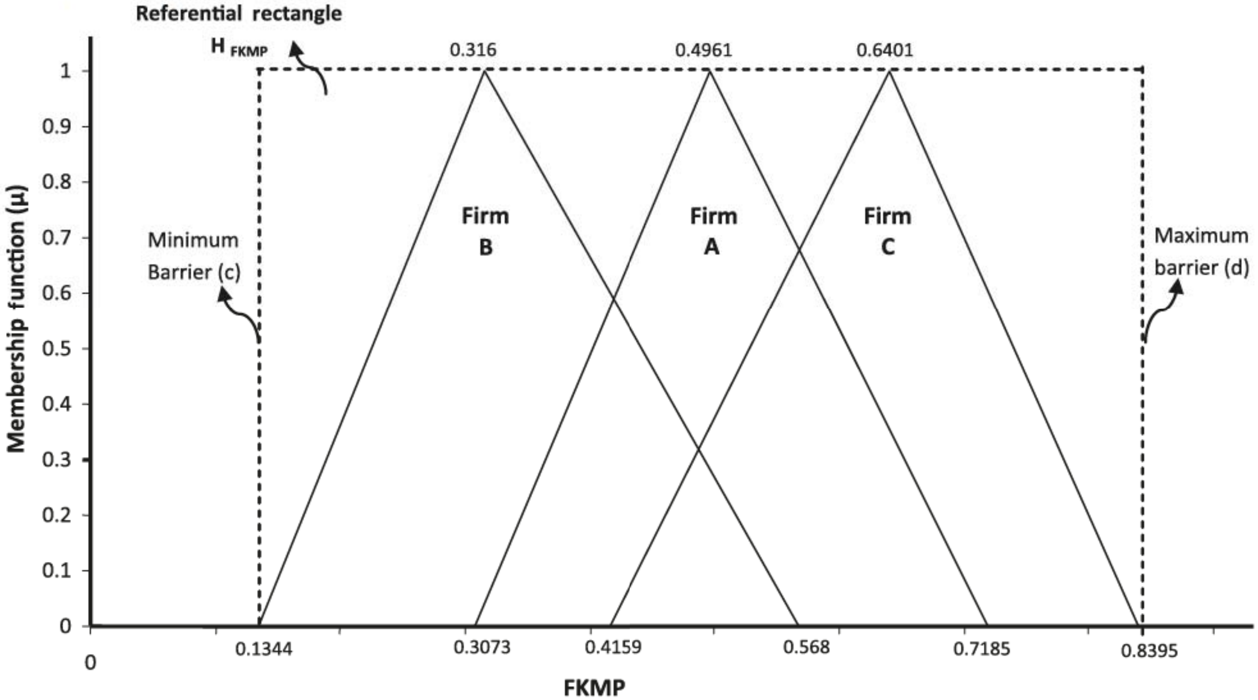
Similarly, The triangular fuzzy numbers associated with the linguistic terms used to measure evaluators' satisfaction with achievement for each item were set as CU = (0,0,0.2); SU = (0,0.2,0.4); MU = (0.2,0.4,0.6); SS = (0.4,0.6,0.8); MS = (0.6,0.8,1.0); and CS = (0.8,1.0,1.0). Fuzzy triangular numbers representing each evaluator's subjective judgments regarding performance ratings of each sub-criterion ($R_{ij,m}$) were then aggregated using eq. [4]. The rationale behind this process was to obtain the average fuzzy performance ratings ($R_{ij,m}$) corresponding to each sub-criterion. Table 1 presents the fuzzy average performance ratings of level 2 criteria of construction firms ($R_{ij,m}$).

The fuzzy knowledge management performance (FKMP) represents a construction firm's overall knowledge management performance. Therefore, it requires a two-stage consolidation of the fuzzy weights and ratings of level 1 ($R_{i,m}$) and level 2 ($R_{ij,m}$) criteria (Table 1) of each construction firm. The commercial optimization software LINGO 9.0 was used in this process. The average fuzzy importance weights (W_{ij}) and the average fuzzy performance ratings ($R_{ij,m}$) of level 2 criteria (sub-criteria) were consolidated in the first stage by using eq. [5]. This consolidation process involved converting eq. [5] into two linear programming models in the form of eqs. [A3*a*] and [A3*b*] (Appendix A) and solving them for three different α-cuts (q = 3 and α = 0.00, 0.50, and 1.00). The consolidation procedure used in computing the fuzzy weighted average performance rating of the knowledge management enablers ($R_{1,\mathrm{A}}$) of construction firm A is illustrated in Appendix B.

The fuzzy-weighted average performance ratings ($R_{i,m}$) of level 1 criteria (C_i) of each construction firm and the average fuzzy importance weights (W_i) of level 1 criteria are presented in Table 1. The fuzzy knowledge management performance (FKMP_m) of each construction firm was calculated in the second stage by converting eq. [6] into linear programming models in the form of eqs. [A3*a*] and [A3*b*] and solving these equations for three different α-cuts (α = 0.00, 0.50, and 1.00). The FKMP_m values for the three construction firms [$\mathrm{FKMP_A}$ = (0.3073,0.4961,0.7185), $\mathrm{FKMP_B}$ = (0.1344,0.3160,0.5680), and $\mathrm{FKMP_C}$ = (0.4159,0.6401,0.8395)] are presented in Fig. 3. For possibility level α = 0, the knowledge management performance of construction firm A ranged from 0.3073 to 0.7185 (Fig. 3). This range shows that the knowledge management performance of construction firm A was not greater than 0.7185 and was not lower than 0.3073. This range highlights the degree of uncertainty regarding the knowledge management performance of the firm. For the possibility level α = 1.00, the knowledge management performance of construction firm A is 0.4961. This value is the most likely value of the knowledge management performance for construction firm A.

The next stage in the benchmarking process is to rank the fuzzy knowledge management performances (FKMP_m) of the construction firms. The FKMP values of the three construc-

Fig. 3. Fuzzy knowledge management performance index (FKMP) of construction firms.



tion firms were ranked using eq. [7]. Construction firm C has the highest ranking index [$I(\mathrm{FKMP_C}) = 0.660$], whereas construction firm B has the lowest ranking index [$I(\mathrm{FKMP_B}) = 0.333$]. These results suggest that construction firm C has the highest knowledge management performance, while construction firm B has the lowest knowledge management performance. Case firm A was ranked second among the three construction firms [$I(\mathrm{FKMP_A}) = 0.519$]. The ranking of the fuzzy knowledge management performances of the construction firms points out that the knowledge management practices of construction firm C should be used in benchmarking knowledge management practices of case firm A.

Fuzzy performance ratings of knowledge management enablers and knowledge management processes ($R_{i,m}$) of the three construction firms were ranked by using eq. [8]. The rationale behind this process was to diagnose performance gaps at the main criteria level. Table 2 presents ranking indices of knowledge management practices [$I(R_{i,m})$] for level 1 criteria (i.e., main criteria). It is clear from Table 2 that the performance ratings of knowledge management enablers and processes of construction firm A are lower than those of construction firm *C* [$I(R_{1,\mathrm{A}}) < I(R_{1,\mathrm{C}})$ and $I(R_{2,\mathrm{A}}) < I(R_{2,\mathrm{C}})$] (Table 2). Therefore, negative performance gaps at the main criteria level are present for construction firm A. The negative performance gap for the knowledge management processes (C_2) is marginal [$I(R_{2,\mathrm{A}}) - I(R_{2,\mathrm{C}}) = -0.057$] for construction firm A, whereas the negative performance gap for the knowledge management enablers (C_1) is substantial [$I(R_{1,\mathrm{A}}) - I(R_{1,\mathrm{C}}) = -0.239$] (Table 2). It appears that construction firm A's knowledge management processes and knowledge management enablers are minor and major weaknesses, respectively. Therefore construction firm A should immediately initiate a managerial action plan to improve its major weakness, i.e., knowledge management enablers. Construction firm A can obtain important diagnostic information for use in developing a managerial action plan to improve its knowledge management enablers by computing the ranking index of each sub-criterion (C_{ij}) and conducting gap analysis for each sub-criterion (C_{ij}). Therefore, fuzzy performance ratings of sub-criteria were ranked by using eq. [9]. Table 3 presents fuzzy performance ratings and ranking indices of knowledge management practices at sub-criteria level (C_{ij}). The values of ranking indices point out that negative performance gaps plague the sub-criteria (C_{ij}) performance ratings of construction firm A, which has a poorer performance than construction firm C on five out of seven sub-criteria (Table 3). Table 3 reveals that organizational culture of construction firm A has the highest negative performance gap [$I(P_{1.3,\mathrm{A}}) - I(P_{1.3,\mathrm{C}}) = -0.238$]. It appears that the organizational culture of construction firm A does not provide an environment that supports the knowledge management activities of its employees. Therefore, construction firm A should focus on improving its organizational culture.

The organizational structure of construction firm A also has a negative performance gap [$I(P_{1.2,\mathrm{A}}) - I(P_{1.2,\mathrm{C}}) = -0.135$] (Table 3). Therefore, construction firm A should redesign its organizational structure to facilitate knowledge management activities. Information and communication technology of construction firm A also has a negative performance gap [$I(P_{1.1,\mathrm{A}}) - I(P_{1.1,\mathrm{C}}) = -0.064$]. Even so, immediate managerial action is not required because the performance gap is marginal. Enhancing the performance rating of organizational culture can improve the major weakness, i.e., knowledge management enablers, of construction firm A.

Table 3 reveals the presence of a negative performance gap in knowledge protection of construction firm A [$I(P_{2.4,\mathrm{A}}) - I(P_{2.4,\mathrm{C}}) = -0.225$]. Enhancing the performance rating in knowledge protection can improve a minor weakness of construction firm A (i.e., knowledge management processes). Similarly, the performance rating for the knowledge acquisi-

Table 2. Performance gap analysis at main criteria (C_i) level.

Main criteria	Construction firm: A, Ranking index $I(R_{i,A})$	B (rival 1), Ranking index $I(R_{i,B})$	C (rival 2), Ranking index $I(R_{i,C})$	Ranking of construction firms	Performance gap for construction firm A $[I(R_{i,A}) - I(R_{i,C})]$
C_1	0.504	0.232	0.743	C, A, B	–0.239
C_2	0.553	0.421	0.610	C, A, B	–0.057

Table 3. Performance gap analysis at sub-criteria (C_{ij}) level.

Sub criteria	Construction firm: A (case firm), Ranking index $I(P_{ij,A})$	B (rival 1), Ranking index $I(P_{ij,B})$	C (rival 2), Ranking index $I(P_{ij,C})$	Ranking of construction firms	Performance gap for construction firm A $[I(P_{ij,A}) - I(P_{ij,C})]$
$C_{1.1}$	0.483	0.236	0.547	C, A, B	–0.064
$C_{1.2}$	0.421	0.263	0.556	C, A, B	–0.135
$C_{1.3}$	0.420	0.219	0.658	C, A, B	–0.238
$C_{2.1}$	0.468	0.423	0.491	C, A, B	–0.023
$C_{2.2}$	0.523	0.314	0.521	A, C, B	0.002
$C_{2.3}$	0.474	0.445	0.473	A, C, B	0.001
$C_{2.4}$	0.258	0.232	0.483	C, A, B	–0.225

tion process of construction firm A $[I(P_{2.1,\ A}) - I(P_{2.1,\ C}) = -0.023]$ is marginally smaller than that of construction firm C, and immediate managerial action is not required.

Construction firm A has positive performance gaps on only two knowledge management practices, i.e., knowledge conversion and knowledge application processes (Table 3). Yet, these positive performance gaps are marginal, so they cannot be considered as major strengths of construction firm A.

Three post-study interviews with the construction firms' executives were conducted to verify the results of the proposed model. The executives considered whether the proposed model offers a practical and useful procedure to evaluate and, in turn, improve their knowledge management practices. They agreed that the power of the model is its ability: (1) to provide a structured approach for understanding and evaluating knowledge management performance and (2) to pinpoint where their strengths and weaknesses lay in knowledge management practices. The executives of the case study firm indicated that they would initiate a managerial improvement plan based on the benchmarking study results.

The proposed benchmarking model has some limitations. First the proposed model performed well for benchmarking the case firm's knowledge management practices, but this provides limited proof of the applicability of the proposed model to other firms or contexts. Second, the proposed benchmarking model was based on a cross-sectional data collection procedure (i.e., a single point in time). Using cross-sectional data collection precludes establishing definitive conclusions regarding the causal relationship between model variables (e.g., knowledge management effectiveness and knowledge management practices). Third, the results of the proposed benchmarking model are based on a self-reporting (subjective) procedure. Self-reporting in a competitive benchmarking study requires providing: (1) a strong belief that information exchanged through a competitive benchmarking study can produce beneficial results to all participants and (2) a strong assurance of confidentiality and anonymity of the results. Although the authors acted based on these requirements, it is possible that overlooking any of these requirements might influence the results of the case study. Fourth, competitive benchmarking is a relatively simple but powerful approach for identifying a firm's advantages and disadvantages relative to competition. Therefore it presents important information regarding relative performance but not absolute performance. Furthermore copying the practices of rival firms, however, may not always lead to increased competitive advantage or significant improvements. Further research is necessary to validate the proposed benchmarking model. Validating the proposed model could include firms of different size and type.

Conclusions and implications

There is increasing recognition that knowledge management is a key capability for construction firms in today's business environment. Therefore, construction firms should develop or use models, tools, and techniques that can enable them to evaluate and improve their knowledge management skills. The research presented here proposes a benchmarking model to address these issues. It builds on the concept of benchmarking, knowledge management models, and fuzzy set theory. The model proposed in this paper can be used by construction firms as an internal performance measurement tool to evaluate their knowledge management performance, identify performance gaps in their knowledge management practices, and identify those knowledge management practices that need improvement to succeed in the future. The iterative process of identifying, rating, and weighting knowledge management criteria helps strategic leaders to understand which knowledge management enablers and processes are important and how knowledge management processes and enablers are linked to their firm's knowledge management performance.

The proposed model presents some advantages in comparison with previous knowledge management performance models that have been published in the construction management literature. First, the proposed model uses competitive dynamics to evaluate a construction firm's knowledge management performance, whereas previous research in construction management ignored competitive dynamics and focused solely on evaluating a construction firm's knowledge management performance. Second, the proposed model is based on fuzzy set theory, a rare approach in this field of research. Most of the information that has been used previously to evaluate knowledge management performance (i.e., the importance weights of each criterion and a firm's achievement level on each criterion) is imprecise, vague, and uncertain. Fuzzy set theory is a flexible tool that can adequately handle uncertainty, imprecision, and vagueness. Therefore, the proposed model provides the flexibility and robustness needed by executives in the construction business to better understand the interrelationships between knowledge management practices. Third, the proposed model provides more information about the ability of a construction firm to achieve its strategic objectives than previous models that use crisp values. The knowledge management performance expressed by triangular fuzzy numbers provides information regarding not only the most possible value but also the lowest and highest values in a range defined by = 0.00–1.00.

Developing a computer program that can facilitate the implementation of the proposed model should be the focus of future research.

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Appendix A

The algorithm proposed by Kao and Liu (2001) to compute fuzzy weighted average is based on α-cuts. The fuzzy weighted average can be defined as: $Y = \sum_{i=1}^{n} W_i R_i / \sum_{i=1}^{n} W_i$

The lower and upper bounds of Y at a specific α-cut can be solved as:

[A1*a*] $$Y_\alpha^L = \min y = \sum_{i=1}^{n} w_i r_i / \sum_{i=1}^{n} w_i$$
$$\text{s.t. } (W_i)_\alpha^L \le w_i \le (W_i)_\alpha^U, i = 1, ..., n$$
$$(R_i)_\alpha^L \le r_i \le (R_i)_\alpha^U, \; i = 1, ..., n$$

[A1*b*] $$Y_\alpha^U = \max y = \sum_{i=1}^{n} w_i r_i / \sum_{i=1}^{n} w_i$$
$$\text{s.t. } (W_i)_\alpha^L \le w_i \le (W_i)_\alpha^U, i = 1, ..., n$$
$$(R_i)_\alpha^L \le r_i \le (R_i)_\alpha^U, \; i = 1, ..., n$$

The minimum of Y occurs at $(R_i)_\alpha^L$ and the maximum of Y $(R_i)_\alpha^U$. Thus, eqs. [A1*a*] and [A1*b*] are simplified to the following fractional programs:

[A2*a*] $$Y_\alpha^L = \min y = \sum_{i=1}^{n} w_i (R_i)_\alpha^L / \sum_{i=1}^{n} w_i$$
$$\text{s.t. } t(W_i)_\alpha^L \le w_i \le t(W_i)_\alpha^U, \; i = 1, ..., n$$

[A2*b*] $$Y_\alpha^L = \max y = \sum_{i=1}^{n} w_i (R_i)_\alpha^U / \sum_{i=1}^{n} w_i$$
$$\text{s.t. } t(W_i)_\alpha^L \le w_i \le t(W_i)_\alpha^U, \; i = 1, ..., n$$

Using the Charnes and Cooper (1962) transformation method by letting $t = 1/\sum_{i=1}^{n} w_i$and $v_i = tw_i$, eqs. [A2*a*] and [A2*b*] can be transformed to the conventional linear program of the following form:

[A3*a*] $$(Y)_\alpha^L = \min y = \sum_{i=1}^{n} w_i (R_i)_\alpha^L$$
$$\text{s.t. } t(W_i)_\alpha^L \le w_i \le t(W_i)_\alpha^U, \; i = 1, ..., n$$
$$\sum_{i=1}^{n} w_i = 1$$
$$t \ge 0$$

[A3*b*] $$(Y)_\alpha^U = \max y = \sum_{i=1}^{n} w_i (R_i)_\alpha^U$$
$$\text{s.t. } t(W_i)_\alpha^L \le w_i \le t(W_i)_\alpha^U, \; i = 1, ..., n$$
$$\sum_{i=1}^{n} w_i = 1$$
$$t \ge 0$$

By enumerating different values α values, the membership function of Y can be constructed.

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Appendix B

Fuzzy average performance rating of knowledge management enablers (R_1) for the construction firm (A) can be calculated as follows:

$$R_{1,\mathrm{A}} = \left(\sum_{j=1}^{3} R_{1j,\mathrm{A}} \otimes W_{1j} \right) \oslash \sum_{j=1}^{3} W_{1j}$$

$$(R_1)_\alpha = [(R_1)^L_\alpha, (R_1)^U_\alpha] = [0.4321 + 0.1502\alpha, 0.7338 - 0.1515\alpha]$$
$$(R_2)_\alpha = [(R_2)^L_\alpha, (R_2)^U_\alpha] = [0.3122 + 0.1582\alpha, 0.6473 - 0.1769\alpha]$$
$$(R_3)_\alpha = [(R_3)^L_\alpha, (R_3)^U_\alpha] = [0.3243 + 0.1491\alpha, 0.6643 - 0.1909\alpha]$$
$$(W_1)_\alpha = [(W_1)^L_\alpha, (W_1)^U_\alpha] = [0.2333 + 0.1667\alpha, 0.5667 - 0.1667\alpha]$$
$$(W_2)_\alpha = [(W_2)^L_\alpha, (W_2)^U_\alpha] = [0.3000 + 0.2000\alpha, 0.7000 - 0.2000\alpha]$$
$$(W_3)_\alpha = [(W_3)^L_\alpha, (W_3)^U_\alpha] = [0.5333 + 0.1667\alpha, 0.8667 - 0.1667\alpha]$$

For $\alpha = 0$

$$\min f_L(W_1, W_2, \ldots\ldots, W_n) = \frac{0.4321W_1 + 0.3122W_2 + 0.3243W_3}{W_1 + W_2 + W_3}$$
$$\begin{aligned} s.t.\quad & 0.2333 \le W_1 \le 0.5667 \\ & 0.3000 \le W_2 \le 0.7000 \\ & 0.5333 \le W_3 \le 0.8667 \end{aligned}$$

$$\max f_L(w_1, w_2, \ldots\ldots, w_n) = \frac{0.7338W_1 + 0.6473W_2 + 0.6643W_3}{W_1 + W_2 + W_3}$$
$$\begin{aligned} s.t.\quad & 0.2333 \le W_1 \le 0.5667 \\ & 0.3000 \le W_2 \le 0.7000 \\ & 0.5333 \le W_3 \le 0.8667 \end{aligned}$$

For $\alpha = 0.5$

$$\min f_L(W_1, W_2, \ldots\ldots, W_n) = \frac{0.5072W_1 + 0.3913W_2 + 0.3989W_3}{W_1 + W_2 + W_3}$$
$$\begin{aligned} s.t.\quad & 0.3167 \le W_1 \le 0.4834 \\ & 0.4000 \le W_2 \le 0.6000 \\ & 0.6167 \le W_3 \le 0.7834 \end{aligned}$$

$$\max f_L(W_1, W_2, \ldots\ldots, W_n) = \frac{0.6581W_1 + 0.5589W_2 + 0.5689W_3}{W_1 + W_2 + W_3}$$
$$\begin{aligned} s.t.\quad & 0.3167 \le W_1 \le 0.4834 \\ & 0.4000 \le W_2 \le 0.6000 \\ & 0.6167 \le W_3 \le 0.7834 \end{aligned}$$

For $\alpha = 1$

$$\max \text{ or } \min\ f_L(W_1, W_2, \ldots\ldots, W_n) = \frac{0.5823W_1 + 0.4704W_2 + 0.4734W_3}{W_1 + W_2 + W_3}$$
$$\begin{aligned} s.t.\quad & 0.4000 \le W_1 \le 0.4000 \\ & 0.5000 \le W_2 \le 0.5000 \\ & 0.7000 \le W_3 \le 0.7000 \end{aligned}$$

The above nonlinear fractional programming problems can be converted into the following linear programming problems:

For $\alpha = 0$

$$\min\ 0.4321W_1 + 0.3122W_2 + 0.3243W_3$$
$$\begin{aligned} s.t.\quad & 0.2333z \le W_1 \le 0.5667z \\ & 0.3000z \le W_2 \le 0.7000z \\ & 0.5333z \le W_3 \le 0.8667z \\ & W_1 + W_2 + W_3 = 1 \\ & z \ge 0 \end{aligned}$$

$$\max\ 0.7338W_1 + 0.6473W_2 + 0.6643W_3$$
$$\begin{aligned} s.t.\quad & 0.2333z \le W_1 \le 0.5667z \\ & 0.3000z \le W_2 \le 0.7000z \\ & 0.5333z \le W_3 \le 0.8667z \\ & W_1 + W_2 + W_3 = 1 \\ & z \ge 0 \end{aligned}$$

For $\alpha = 0.5$

$$\min\ 0.5072W_1 + 0.3913W_2 + 0.3989W_3$$
$$\begin{aligned} s.t.\quad & 0.3167z \le W_1 \le 0.4843z \\ & 0.4000z \le W_2 \le 0.6000z \\ & 0.6167z \le W_3 \le 0.7834z \\ & W_1 + W_2 + W_3 = 1 \\ & z \ge 0 \end{aligned}$$

$$\max\ 0.6581W_1 + 0.5589W_2 + 0.5689W_3$$
$$\begin{aligned} s.t.\quad & 0.3167z \le W_1 \le 0.4843z \\ & 0.4000z \le W_2 \le 0.6000z \\ & 0.6167z \le W_3 \le 0.7834z \\ & W_1 + W_2 + W_3 = 1 \\ & z \ge 0 \end{aligned}$$

For $\alpha = 1$

$$\max \text{ or } \min\ 0.5823W_1 + 0.4704W_2 + 0.4734W_3$$
$$\begin{aligned} s.t.\quad & 0.4000z \le W_1 \le 0.4000z \\ & 0.5000z \le W_2 \le 0.5000z \\ & 0.7000z \le W_3 \le 0.7000z \\ & W_1 + W_2 + W_3 = 1 \\ & z \ge 0 \end{aligned}$$

The above presented linear programming problems were solved by using commercial linear programming software. The desired interval for $\alpha = 0.00$, $\alpha = 0.50$ and $\alpha = 1.00$ are [0.3336, 0.6888], [0.4164, 0.5950] and [0.4997, 0.4997], respectively. Therefore fuzzy average performance rating $(R_{1,A})$ of construction firm A is [0.3336, 0.4997, 0.6888].