



An integrated proactive knowledge management model for enhancing engineering services

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ARTICLE INFO

Article history:

Accepted 16 February 2012

Available online 15 March 2012

Keywords:

Engineering consulting
Knowledge management
Proactive problem-solving
Business intelligence

ABSTRACT

More and more construction organizations have adopted Knowledge Management (KM) to enhance their engineering services. However, most of the traditional KM methods suffer from their “reactive mode” of problem solving. To cope with this problem, a newly developed model, the Integrated Proactive Knowledge Management Model (IPKMM), is proposed in this paper. A leading engineering consulting firm in Taiwan was selected as a case study to implement the proposed model. The system implementation of IPKMM, the Integrated Proactive Knowledge Management System (IPKMS), is verified with real world cases. A novel Business Intelligence Index (BII) is also proposed in this paper to evaluate the relative competitiveness of different KM models. It is confirmed from the case study that IPKMM can significantly improve the efficiency of problem-solving and the competitiveness of an engineering consulting firm in the service market. This study demonstrates that IPKMM has great potential in enhancing emergent problem-solving for engineering consultants.

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1. Introduction

Construction is a knowledge-intensive industry and an experience-based discipline. It relies heavily on the knowledge and experience accumulated from previous projects. In Taiwan and many other countries, engineering consulting firms have developed their own Knowledge Management Systems (KMSs) to enhance the firms' Knowledge Management (KM) initiatives in the past decade. The traditional KMSs adopt Communities of Practice (COPs) as an important means of knowledge generation, sharing, exchanging, storing, and retrieving. A COP is defined as a group of people informally bound together by shared expertise and passion for a joint enterprise [1]. Emergent problem solving is an important application of the COP in engineering services. Problem solving is related to almost all kinds of engineering services including proposal preparation, feasibility studies, architectural and engineering designs, procurement, construction supervision, and project management.

A problem-solving process in a KMS is usually divided into two stages: (1) a problem is posed by a COP member (the questioner); then (2) other members (the responders) read the description of

the problem and provide their solutions voluntarily. The essential problem for such a problem-solving approach is that the raised problem should wait for the responder (the so-called “domain expert”) who has the expertise or knowledge to solve the problem, to provide solutions. However, the domain experts are not always available to answer problems immediately. They may not see the raised problem or they may be too busy to answer the problem in time. Although previous research has improved this drawback by developing an emergent problem-solving system (called the SOS system)[2], it was found that the average waiting time for the raised problems to be solved by domain experts is 2.68 days [3]. Such a Reactive Problem-Solving (RPS) approach is inefficient in timeliness and cost effectiveness. It is unacceptable for many emergent problems that require prompt responses, such as construction disasters or crises happening on site. Even for other problems, instant answering will undoubtedly improve the satisfaction of the clients. Hence, to shorten the problem-solving duration is very desirable in engineering consulting services.

Yu et al. [4] have identified the key barrier that causes the delay of problem solving as the “reactive mode” of KM. That is, the problem raised by the questioner has to wait (passively) for responses from members of the COP in a KMS. Such a passive/reactive mode is related to the original design of the “knowledge creation organization” in Nonaka's theory [5]. Such a barrier needs to be broken in order to improve the timeliness of problem solving and thus enhance the engineering services of a consulting firm.

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The presented research aims at enhancing engineering services through the Integrated Proactive Knowledge Management Model (IPKMM). The proposed IPKMM consists of an Enhanced Proactive Problem Solver (EPPS), which is based on the previously developed Model of Proactive Problem Solver (MPPS), a Knowledge Value Adding System (KVAS), and an Intellectualization System (IS). The integration of the abovementioned subsystems provides required functions for a proactive problem solver. A prototype system called the Integrated Proactive Knowledge Management System (IPKMS) that implements the proposed IPKMM has been developed and integrated with the existing KMS of a leading engineering consulting firm in Taiwan. A quantitative measure, namely the Business Intelligence Index (BII), is defined to evaluate the performance of the proposed IPKMM in enhancing the engineering services of an engineering consulting firm. Besides, several quantitative experiments for evaluating the performance of the proposed method are also conducted.

The rest of the paper is organized as follows. In Section 2, previous research by the research team and other teams related to IPKMM is revisited following the introduction in order to provide the required backgrounds. In Section 3, the proposed IPKMM is described in detail. In Section 4, the IS system is demonstrated. In Section 5, a set of comprehensive quantitative experiments are conducted to evaluate the performance of the proposed IS. In Section 6, the BII is defined and employed to evaluate the proposed IPKMM. Finally, conclusions and recommendations are addressed in Section 7.

2. Review of related works

In recent years, Knowledge Management (KM) has been recognized as a core business concern and many KM related approaches have been proposed to enhance the performance of engineering services. Since construction is an experience-based discipline, KM in the construction industry plays a very important role. New works can be solved efficiently by reusing the knowledge and experience accumulated from previous projects [6]. Hence, the business performance can be improved and the competitive advantage can be gained. In the construction industry, more and more companies have developed their own Knowledge Management Systems (KMSs) [6–8]. It has been proved that the firms have received benefits from the KMS implementations.

On the other hand, due to the contracting nature, fragmented organization, uncertain environment, and the changeable construction site, construction managers and engineers are faced with emergent problems and crises in their daily business operations [2]. Problem-solving has become the fundamental activities in construction management [9–12]. Previous researchers have pointed that the specific characteristics of construction problems need to be tackled in order to solve them quickly, correctly, and cost-effectively. Such characteristics include [9,12]: the ill-structure nature, inadequate vocabulary, little generalization and conceptualization, and temporary multi-organization. Apart from the nature of construction problems, Dave and Koskela [13] noted that industry fragmentation and the ad-hoc nature of construction projects further complicate the capture and reuse of valuable knowledge. Such a nature results in “dynamic knowledge” that needs constant updating to create new practices to achieve enhanced solutions [14]. Such a complicated nature has made the adoption of KMS in a construction organization unique compared with that in the other industries. In the following, we review some related works and experiences of the research team gained from the applications of KMS in an engineering consulting organization. Such works provide required backgrounds of the proposed Integrated Proactive Knowledge Management Model (IPKMM) in this paper.

2.1. Emergency problem solving system

In 2002, China Engineering Consultants, Inc. (CECI) developed an integrated system that combined the Knowledge Management

System (KMS) with an emergency problem-solving system (called the SOS system), namely the Knowledge Management integrated Problem-Solver (KMiPS) [2]. The SOS is a special subsystem of the KMS, which provides a tentative forum for solving emergency problems encountered by engineers/managers. Once the problem is posed as an SOS-problem, it is posted on the SOS board on the portal page of the KMS for emergent discussion. Such an arrangement forces every member of the KMS to take a look at the posed problem whenever he/she logs on. As a result, it generally receives attentions and usually has a better chance of being solved by responders. Problems posted on the SOS board which receive no response within one working day (24 h) will be automatically removed and transferred to the relevant Communities of Practice (COPs). After this, it becomes a regular topic for discussion in the relevant COPs.

The KMiPS demonstrated its capability in the improvement of the effectiveness of KMS for problem solving. It was measured by Yu et al. that the average time benefit of KMiPS is 63%; the average man-hour benefit is 73.8%; and the average cost benefit is 86.6% [15]. In another study, it was found that the KMiPS has shortened the average problem-solving time for emergency problems from 5.54 days to 2.68 days [3,6]. The underlying reason for this improvement in time effectiveness is the Medici's Effect [16] that brings together experts of all relevant disciplines and provides a forum for intersections of the domain experts with different contexts.

2.2. The Performance Improvement Strategy Planning (PISP) Model

Yu et al. [11] proposed a model called Performance Improvement Strategy Planning (PISP) that combines a Knowledge-management-activity Surveying Module (KSM), a Benefit Quantification Module (BQM), a Performance Data-mining Module (PDM), and a Strategy Planning Module (SPM) to form an integrated system that suggests performance improvement strategies systematically. With the mass performance data measured by BQM, the Data Mining (DM) techniques can be applied to find out effective strategies such as: “Development of a Pre-selection Mechanism” to screen out the insignificant problems, “Setup of a Warning System” to avoid wasting members' time on unsolvable problems [17].

The study of PISP also suggests building an “Expert Map” to direct the emergency problem to the most relevant domain experts, and developing “Lesson-Learned Files” for questioners to find the solution directly. The above strategies suggest the need for a “proactive mode” of problem solving [17] which: (1) searches for a solution to the problem from previous lessons learned first; or (2) if the solution is not found, directs the problem to the most appropriate domain expert who knows the solution best. The abovementioned ideas resulted in the development of the Model of Proactive Problem-Solving (MPPS) [4].

2.3. Model of Proactive Problem-Solving (MPPS)

The MPPS was proposed to improve the drawbacks of the traditional reactive mode of KM [17]. The MPPS consists of four major components: (1) a Knowledge/Expert Map (K/EMap)—providing a classification scheme for the knowledge and expertise of the domain experts; (2) an Automatic Problem Answering (APA) module—solving the posed problem automatically based on the historic problem-solving cases and lessons-learned; (3) an Automatic Problem Dispatching (APD) module—dispatching the posed problem to the most appropriate domain expert when the problem was not solved by APA; (4) a Lesson-Learned Wizard (LLW)—accumulating historic lessons-learned based on the classification scheme of K/EMap.

The major ideas behind MPPS are: (1) accumulating historic lessons-learned and classifying them according to some coding criteria; (2) identifying the domain experts related to a specific domain based on the classification of previous lessons; (3) searching for

historic solutions before posing problems in the COP; and (4) if the solution is not found, dispatching the problem to the domain experts who are most relevant to the problem.

The major contribution of MPPS is to establish a new framework for KM; however, it was soon discovered that the MPPS cannot work effectively if the historic lessons-learned are not sufficient for the diverse emergent engineering problems encountered by the firm. It is desirable to establish an automated method for collection of historic lessons learned.

3. Proposed Integrated Proactive Knowledge Management Model (IPKMM)

The Integrated Proactive Knowledge Management Model (IPKMM) is composed of three major components: an Enhanced Proactive Problem Solver (EPPS), a Knowledge Value Adding System (KVAS), and an Intellectualization System (IS). The framework of the proposed IPKMM is shown in Fig. 1.

Based on the framework of Model of Proactive Problem Solver (MPPS) [4], an Enhanced Proactive Problem Solver (EPPS) is proposed. The EPPS enhances the Lesson-Learned File (LLF) of the previous MPPS with more comprehensive and general knowledge sources called the Intellectual Asset Repository (IAR) by introducing two new components—the Knowledge Value Adding System (KVAS) and the Intellectualization System (IS)—to automatically collect historical lessons-learned and Knowledge Cases (KCs) recorded in the Communities of Practice (COPs), and to generate the intellectual assets of the IAR. The components of IPKMM are described in the following.

3.1. Enhanced Proactive Problem Solver (EPPS)

The EPPS is the kernel of the IPKMM; it performs the main functions of proactive problem solving. The major components of EPPS are described in the following:

1. Knowledge/Expert Map (K/EMap)

The EPPS is focused on the knowledge and the experts holding the knowledge. In EPPS, the domain knowledge is represented by

Knowledge Map (KMap), while the domain experts are characterized by Expert Map (EMap)[4]. The Knowledge Map and Expert Map (K/EMap) provide the ontology for modeling the knowledge repository of the engineering consulting firm. In this paper, the K/EMap refers, but not limited, to that of the target engineering consulting firm [4]. The K/EMap of the target engineering consulting firm is constructed by a Multi-dimensional Knowledge Ontology (MKO) consisting of three dimensions: lifecycle code, product code, and technical code. 270 engineering areas are contained in the K/EMap, including civil, structural, geotechnic, environmental, transportation, and construction engineering.

2. Automatic Problem Answering (APA) module

The APA [4] is an Automatic Problem-solving System (APS). Once a problem is issued by the questioner, APA will automatically search the IAR to find out the most relevant solutions, and then these solutions are given to the questioner.

3. Automatic Problem Dispatching (APD) module

In the APD module [4], the unsolved problem is automatically dispatched to the most relevant experts. The problem characteristics analyzed in the APA module are used to find the most appropriate domain experts based on the EMap described previously. Then, the problem is dispatched to the most relevant domain experts for a possible solution. Finally, the experts respond to the problem in a special COP called SOS.

4. Intellectual Asset Repository (IAR)

The IAR is an extension of the LLF [4] in the original MPPS. The IAR consists of three major sources of knowledge: (1) LLFs—obtained from previous experiences of problem solving in Knowledge Management Integrated Problem-Solver (KMIPS) and COPs; (2) Knowledge Cases (KCs)—a compilation of the reusable knowledge sharing cases by the KVAS from COPs; (3) Corpuses—the knowledge corpuses generated automatically by the IS.

3.2. Knowledge Value Adding System (KVAS)

The KVAS is comprised of three components [18] (1) the Knowledge Value Adding Survey Module (KVASM)—a web-based questionnaire system that surveys the COP members participating in discussions of

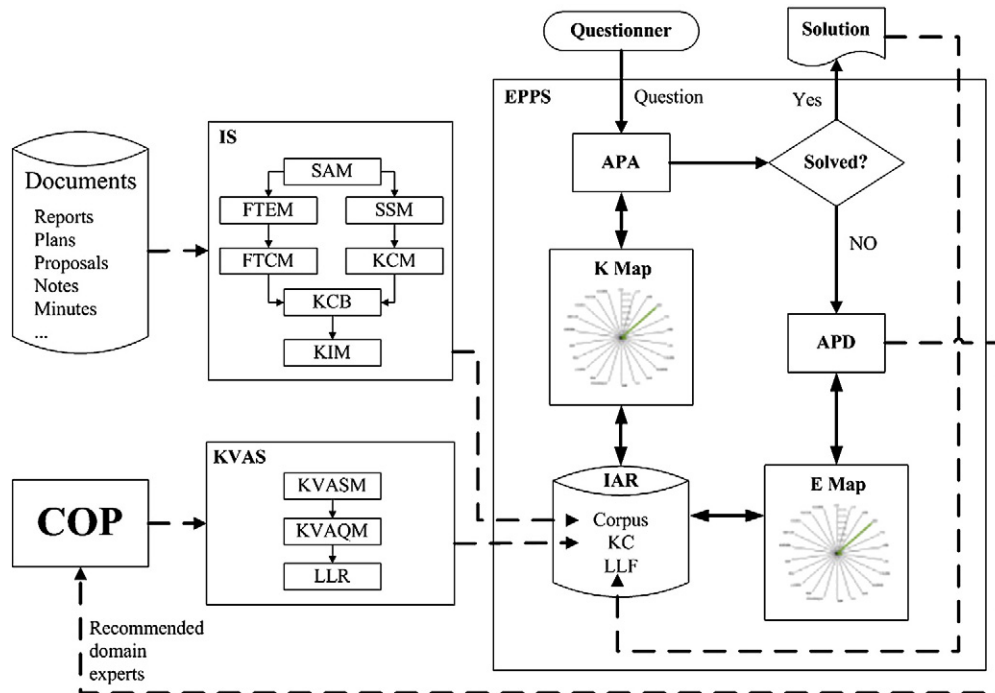


Fig. 1. Framework of the Integrated Proactive Knowledge Management Model (IPKMM).

problem-solving or knowledge-sharing processes; (2) the Knowledge Value Adding Quantification Module (KVAQM)—a module that generates Knowledge Value Adding (KVA) values by quantification of KM performance with the questionnaire survey results; and (3) the Lesson-Learned Recorder (LLR)—a computer aided information system that helps the COP members to compile and record previous learned knowledge, named Lesson-Learned Files (LLFs), that is useful to solve future problems. The outputs of KVAS are: (1) the Lesson-Learned Files (LLFs) and Knowledge Cases (KCs); and (2) the calculated Knowledge Value Adding (KVA) values associated with all surveyed cases and the participants (the domain experts). As the KVA values are calculated, the relevance of a specific LLF/KC and its associated domains (classified codes) is established. The relevance is used in searching for the historic LLF/KC for problem solving and finding out the most appropriate domain experts when the solution is not found.

3.3. Intellectualization System (IS)

The IS is a text-mining based corpus generation system that produces knowledge corpuses automatically from existing documents (the explicit knowledge) of the firm, such as final reports, plans, proposals, notes, minutes, etc. The current version of IS can tackle corpus generation tasks for three types of corpuses: (1) a text corpus—the segment of text that contains specialized meaning related to a specific domain; (2) a table corpus—a table that contains special meaning related to a specific domain; and (3) a figure that contains special meaning related to a specific domain. Details of the functionality of the IS are described in Section 4.

3.4. Integrated operations of IPKMM

The integrated operation of the IPKMM is shown in Fig. 1, where the solid arrows show the problem-solving processes and the dashed arrows show the intellectual asset generation processes. The problem-solving process starts with the questioner posing a question in EPPS. The APA of the EPPS searches the KMap to find candidate solutions from the most relevant Intellectual Assets for the questioner. If the questioner is not satisfied with all candidate solutions, the question is diverted to the relevant COP. Simultaneously, the EPPS searches the EMap to find out the most appropriate domain experts, and a message is automatically sent to those experts. The selected experts are requested to respond to the question with their solutions in the COP. Should the problem be solved, the participants in the problem-solving process are surveyed via KVAS, and a new LLF is generated in the IAR.

4. Knowledge extraction through the Intellectualization System

As addressed at the end of Section 2, the critical bottleneck of problem-solving process in the previously developed Model of Proactive Problem Solver (MPPS) was due to the insufficient Lesson-Learned Files (LLFs) to provide acceptable solutions for the questioners. This is resolved in the Integrated Proactive Knowledge Management Model (IPKMM) with the Intellectualization System (IS), which can extract explicit knowledge (namely knowledge corpuses), represented as text, table or figure corpuses, from engineering documents such as the project's final reports, plans, proposals, and other knowledge documents. Three types of knowledge corpuses are generated by IS, i.e., text, table and figure corpuses.

The text corpuses are generated via the following steps: (1) analyzing the structure of the document with the Structure Analysis Module (SAM); (2) the structured document is segmented into corpuses with the Semantic Segmentation Module (SSM); (3) the corpuses are classified with the Knowledge Categorization Module (KCM); (4) the classified corpuses are stored in the Knowledge Corpus Base (KCB); and (5) finally, the corpuses stored in KCB are

integrated with other existing corpuses by the Knowledge Integration Module (KIM).

The table and figure corpuses are generated via a similar process, as follows: (1) analyzing the structure of the document with SAM; (2) the figures/tables are extracted with the Figure and Table Extraction Module (FTEM); (3) the figures/tables are classified with the Figure and Table Categorization Module (FTCM); (4) the classified figure/table corpuses are stored in KCB; and (5) finally, the figure/table corpuses stored in KCB are integrated with existing corpuses by the Knowledge Integration Module (KIM).

4.1. Structure Analysis Module (SAM)

In the Structure Analysis Module (SAM), headings of chapters and sections (such as “Chapter 1 Introduction”) included in a knowledge document are extracted and organized as a structured list of content with multiple levels. The structured list of headings is useful for users to grasp the overall structure of the document.

To implement SAM, existing Microsoft Office® Word functions are employed to extract predefined headings, which are defined by the authors through Microsoft Office® Word built-in functions, such as Bullet and Style. However, according to the examples collected for the case study, most of the documents in the real world contain no predefined headings. Authors usually key in the headings manually, instead of using the Microsoft Office® Word functions. In such cases, headings are not able to be extracted by Microsoft Office® Word functions.

To cope with this problem, a heading extraction method is developed. Firstly, the documents are analyzed. A heading usually consists of “Chapter” or “Section” followed by an ordinal number and a brief description, such as “Chapter 1 Introduction”. In other cases, a heading may only consist of an ordinal number and a brief description, such as “1. Introduction”. The commonly used forms of headings are collected from the documents beforehand. Each of the collected forms of headings is then compiled as a regular expression [19]. This provides a basis for automatically constructing the structured list of a document.

Secondly, each paragraph in a knowledge document is evaluated to decide whether it is a heading or not. If a paragraph is formed as a heading and the paragraph is too short (i.e., the length of the paragraph is less than n words, n is empirically designated), the paragraph will be considered as a heading. To identify whether a paragraph is a heading, the regular expressions are used to match with the paragraph. The paragraph is regarded as a heading if one of the regular expressions matches the form of the paragraph.

Finally, the headings are used to construct the structured list of a document. Each of the headings is assigned a number representing its level in the structured list. The level of a heading is assigned according to its extracted order and the regular expression it matches. For example, the first extracted heading is assigned as level one. If the second extracted heading matches the same regular expression as that of the first heading, the second heading will be assigned as level one as well. Otherwise, the second heading will be assigned as level two, and so forth.

4.2. Semantic Segmentation Module (SSM)

The purpose of semantic segmentation is to divide a document into several shorter segments, with the sentences within a segment sharing a subtopic. Semantic segmentation enables the Automatic Problem Answering (APA) of Enhanced Proactive Problem Solver (EPPS) to provide only the fragment(s) of text that the user is interested in, rather than the whole document. It will save the questioner great effort and time as it is not necessary to read through the whole document.

To segment a document into several thematic segments, topic boundaries between text paragraphs need to be identified. At first, each chapter of a document is divided into the sections and subsections indicated by the author. The regular expressions applied in the Structure Analysis Module (SAM) are used as delimiters to split a document into sections and subsections.

A chapter/section usually consists of several subsections, each of which consists of paragraphs which share the same subtopic. Based on such an observation, the boundaries of subsections are regarded as the topic boundaries, and hence each subsection is regarded as a semantic segment. Finally, all the semantic segments are regarded as knowledge corpuses and saved into Intellectual Asset Repository (IAR).

4.3. Figure and Table Extraction Module (FTEM)

In the Figure and Table Extraction Module (FTEM), both figures and tables included in knowledge documents are also extracted as knowledge corpuses. Extracted figures and tables are correlated with the most relevant semantic segments to provide integrated knowledge corpuses. Hence, knowledge corpuses included in a document could be completely utilized while solving emergent problems.

The process of FTEM can be divided into three stages. Firstly, figures and tables are extracted from knowledge documents. The built-in object model provided by Microsoft Office® Word is employed to extract figures and tables from the knowledge documents. Secondly, figure captions and table captions are extracted. Generally speaking, figure captions are located below figures while table captions are located above tables. For this reason, FTEM uses regular expression to search for paragraphs which include the keyword “Figure” and are short (e.g., the length of the paragraph is less than ten words), located below a figure, as the figure caption. A similar process is conducted for extracting table captions. Finally, the extracted figures, tables, figure captions, and table captions are saved in IAR.

4.4. Knowledge Categorization Module (KCM)

The Knowledge Categorization Module (KCM) is used to classify semantic segments created by SSM. KCM applies Case Based Reasoning (CBR) [20,21] to deduce the knowledge category of a semantic segment. CBR is an artificial intelligence method that finds solution for a new problem by using the previous experience. In KCM, according to the categories of previous Knowledge Cases (KCs) and Lesson-Learned Files (LLFs), which are served as training cases, the knowledge category of each semantic segment can be deduced automatically.

The process of knowledge categorization can be divided into three stages: the similarity between a semantic segment and each training case is firstly determined by the similar method described in Section 4.2. Then the average similarity of each knowledge category (represented with a classification code [6]) is computed. Finally, knowledge categories with the top 3 average similarities are regarded as the knowledge categories of the semantic segment. For example, suppose there is a semantic segment Seg_i created in SSM, the similarities between Seg_i and each knowledge category are computed based on a previously developed algorithm [4] and shown in Table 1. The summarized similarity of each knowledge category is shown in Table 2. The knowledge categories with the top 3 average similarities, “510D15”, “416D80” and “071X10”, are regarded as the knowledge categories of Seg_i .

4.5. Figure and Table Categorization Module (FTCM)

The Figure and Table Categorization Module (FTCM) is used to classify figures and tables according to the knowledge categories of the semantic segments referring to them. For example, suppose

Table 1

Similarities between an example semantic segment Seg_i and each of the knowledge categories.

Case ID	Knowledge category	Similarity
1	416D80	0.4
2	542D15	0.2
3	071X10	0.5
4	542D15	0.2
5	510D15	0.7
6	542D15	0.2

“Fig. 1” is referred to by semantic segments Seg_1 and Seg_2 which belong to the knowledge categories shown in Table 3, the knowledge categories of “Fig. 1” are the union of the knowledge categories of Seg_1 and Seg_2 (i.e., 510D15, 416D80, 071X10 and 542D15).

4.6. Knowledge Integration Module (KIM)

The Knowledge Integration Module (KIM) is used to integrate KCB, KCs, and LLFs into structured knowledge assets containing semantic index. The Vector Space Model (VSM) [22–24] has been the most popular model to represent a document in the field of information retrieval. Due to its popularity, the integration of the unstructured knowledge assets is based on VSM. At first, the original knowledge assets (i.e., KCB, KCs, and LLFs), which are in the form of unstructured natural language discourses, are processed by domain keywords extraction and importance weighting identification. After the processing, each of the unstructured knowledge assets is represented as a *Characteristic Vector*:

$$CV(KA_i) = \{(k_1, w_{i1}), (k_2, w_{i2}), \dots, (k_j, w_{ij}), (k_n, w_{in})\} \quad (1)$$

where $CV(KA_i)$ represents the *Characteristic Vector* of the knowledge asset i ; k_j represents keyword j ; and w_{ij} represents the importance weighting value of k_j in knowledge asset KA_i . The importance weightings of the keywords are calculated by using the Importance Factor (IMF) method [25]. Finally, the characteristic vectors are stored in the IAR as the structured knowledge assets. The knowledge assets are used as the sources for searching solutions in solving future problems.

5. System testing and performance evaluation

A computer system that implements the proposed IPKMM has been developed with the similar name, Integrated Proactive Knowledge Management System (IPKMS). In order to evaluate the problem-solving performance of IPKMS, 200 testing sets were randomly selected from the testing data of our previous work on the Model of Proactive Problem Solver (MPPS) (as mentioned in Section 2.3)[6], where the testing problems were comprised of two different sources: (1) original problem set—consists of the 908 LLFs; and (2) similar problem set—consists of 1304 derived problems, each of which is a similar problem description modified from one of the original LLFs. Totally 1304 similar problems were generated by 63 domain experts who were managers/senior engineers of the case engineering consulting firm. Each problem description of the 908

Table 2

Summarized similarities of the knowledge categories in Table 1.

Knowledge category	Summation of similarity	Average similarity
510D15	0.7	0.7
071X10	0.5	0.5
416D80	0.4	0.4
542D15	$0.2 + 0.2 + 0.2 = 0.6$	$0.6/3 = 0.2$

Table 3
Test sets used for the performance evaluation of IPKMS.

	Type of sample	Description
Test set 1	100 existing problems	The same problems exist in LLFs
Test set 2	100 similar problems	Similar problems as those in test set 1

LLFs was presented to the 63 domain experts to provide 1 to 3 similar but differently articulated problem descriptions for testing.

In this study, the 100 original problems were randomly sampled from the original problem set and denoted as Test Set 1; while the other 100 similar problems were selected from similar problem set and denoted as Test Set 2, which are associated with the selected original problems.

In order to show the benefits of the proposed Intellectualization System (IS) for problem-solving, this study focuses on evaluating the capability of IPKMS in providing the most relevant solutions for each posed problem. In other words, the aim was to validate whether or not IS could nourish the Intellectual Asset Repository (IAR), so that IPKMS could provide the more relevant solutions for each problem. For each of the test sets, two experiments were performed: (1) IPKMS search solutions (through Automatic Problem Answering (APA)) from LLFs only; (2) IPKMS search solutions (through APA) from the IAR which consists of LLFs, Knowledge Cases (KCs), and knowledge corpuses extracted from the engineering documents. Average similarity was adopted as the measure for evaluating the performance of IPKMS:

$$AvgSim = \frac{1}{100} \sum_{i=1}^{100} \sum_{j=1}^n \frac{Sim_{ij}}{n} \quad (2)$$

where Sim_{ij} represents the similarity between problem i and retrieved solution j ; n represents the number of all retrieved solutions.

The evaluation results of IPKMS for the two test sets based on Eq. (2) are shown in Figs. 2 and 3. It is found that the average similarity decreases as n increases. This is expected because the retrieved solutions are sorted by the similarity between problem i and each of the retrieved solutions. The average similarity is highest when only the most relevant solution is retrieved (i.e. $n = 1$) and the average similarity decreases gradually when $n > 1$. More retrieved solutions may lead to lower average similarity, but will improve the performance of problem solving because the user can always find the most relevant solutions from the top n retrieved solutions and can also find more relevant solutions while he/she explores the other solutions.

As can be seen from Figs. 2 and 3, under different n settings, the average similarity is higher when the LLFs, KCs, and knowledge corpuses extracted from the knowledge documents are incorporated in IAR than merely using LLFs. This means that using IPKMS to search

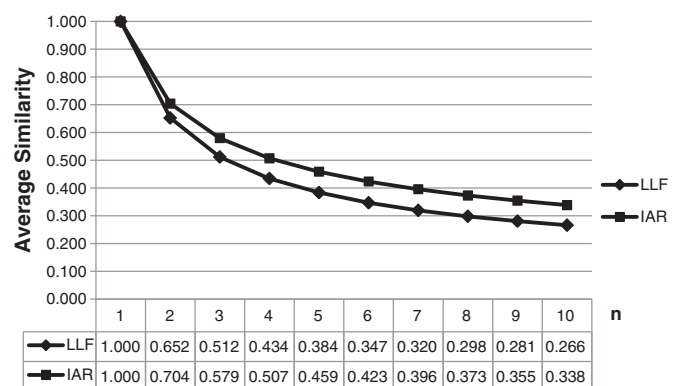


Fig. 2. Comparison of average similarity in test set 1.

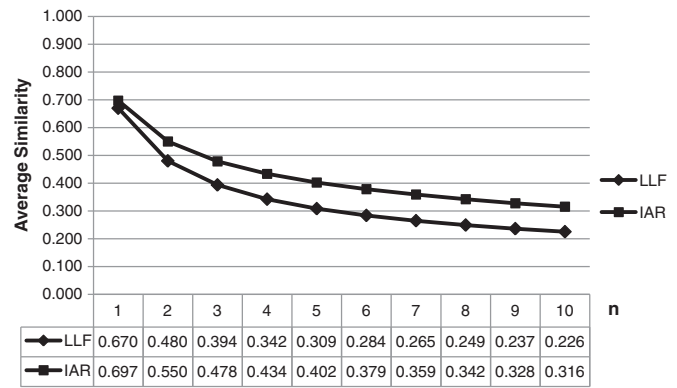


Fig. 3. Comparison of average similarity in test set 2.

for solutions (through APA) from the IAR (comprising LLFs, KCs, and knowledge corpuses) will improve the relevance of the obtained solutions for the posed problems. As a result, the proposed IPKMS is verified to be able to enhance IAR and hence improve construction problem solving.

6. Measurement of organizational business intelligence

In order to measure the business intelligence capacity of an engineering consulting organization, an operational indicator, the Business Intelligence Index (BII) for engineering consulting firms, is defined. The definition of BII and analysis of the problem-solving performance in three different Knowledge Management (KM) implementation phases are described in the following.

6.1. Defining the Business Intelligence Index (BII) for an engineering consulting firm

The proposed Integrated Proactive Knowledge Management Model (IPKMM) and its prototype system, Integrated Proactive Knowledge Management System (IPKMS), have been implemented for the case engineering consulting firm, China Engineering Consultants, Inc. (CECI). In order to evaluate the performance of the proposed IPKMM, a measurement, namely Business Intelligence Index (BII) is defined in Eq. (3) to measure the relative competitiveness of different KM implementations.

$$BII = \frac{[IA(p, i, c)]^S}{T} \quad (3)$$

In Eq. (3), the $IA(p, i, c)$ is the collection of all Intellectual Assets (IAs) that are functions of: (1) the staff of the organization (p); (2) the internal process (i); and (3) the customers (c); S is the “times of knowledge-sharing” (or share number) of the IA, which can be measured by the number of COP members participating in the problem-solving process; T is the responding time required to find the solution.

The numerator of Eq. (3) represents the capacity of intelligence of the organization. According to Nonaka [5] and Johansson [16], more intersections of the people with different contexts shall result in more valuable knowledge creations for problem solving. Due to the leverage of knowledge in Knowledge Management System (KMS), the share number of IA should be exponential in measuring BII. Therefore, more IA will result in a higher BII; a higher share number will increase the BII exponentially. In the proposed IPKMM, there are three types of IAs, as depicted in Fig. 1 and explained in Section 3.1: (1) the Lesson-Learned Files (LLFs) compiled from emergency problem solving system (SOS); (2) the Knowledge Cases (KCs) recorded from the voluntary discussions in COPs; and (3) the

knowledge corpuses that are automatically generated from engineering documents with Intellectualization System (IS).

The denominator of Eq. (3) implies that the shorter responding time will increase the value of BII since problem-solving is always time-constrained. This is especially true for engineering consulting services, since the clients of engineering projects usually require the consultants to respond to their problems promptly. Delays in problem solving will not only dissatisfy the client but also reduce the value of the solution.

The value of BII can be obtained by substituting the estimated values of $IA(p, i, c)$, S , and T into Eq. (3). An illustrative example of BII calculation for the case engineering consulting firm is demonstrated in the following subsection.

6.2. Measuring the BII of the case engineering consulting firm

The BII defined previously is applied to the case engineering consulting firm to measure the problem-solving performance in the three different KM implementation phases: (1) phase with no KM implementation; (2) reactive KM phase; and (3) IPKMM implementation phase. Assume that the IA of the organization is the same for the three periods. Before KM implementation, the problem solving is conducted by group meetings with an average of 4.26 staff members; the number of problem-solving participants increased to 7.14 after KMS was established [3]. To be conservative, here we assume that the implementation of IPKMM involves the same number of staff as the reactive KM period in the problem solving. The responding times for the three periods are on average [3]: 5.54 days before KM implementation and 2.68 days for reactive KM, but about 5 s after IPKMM implementation. Although the reactive KM and IPKMM need additional time to set up a knowledge management system, the installation is conducted only once. In the long term, the set up time can be ignored. Therefore, the set up time required to construct a knowledge management system is not taken into account in the responding times for the three periods. Substituting the above parameters into Eq. (3), the ratios of BII for the traditional approach: BII of reactive KM: BII of IPKMM are shown in Eq. (4):

$$\begin{aligned} BII_{\text{trad.}} : BII_{\text{react.KM}} : BII_{\text{IPKMM}} \\ = \frac{[IA(p, i, c)]^{4.26}}{478,656 \text{ s}} : \frac{[IA(p, i, c)]^{7.14}}{233,280 \text{ s}} : \frac{[IA(p, i, c)]^{7.14}}{5 \text{ s}} \end{aligned} \quad (4)$$

To measure the BII of the case engineering consulting firm more specifically, totally 908 LLFs, 20,045 KCs (from 36 COPs), and 522 knowledge documents were collected from 50 real world projects of the case A/E consulting firm. The LLFs and KCs were collected from Jan. 2005 to Aug. 2009. Finally, 3665 semantic paragraphs (consisting of 70,519 paragraphs), 11,959 figures, and 3223 tables were extracted from 522 knowledge documents by IS.

Substitute “39,800” (the total number of LLFs, KCs, and knowledge corpuses extracted) for the base, IA, then substitute the responding time with 5.54 days, 2.68 days, and 5 s for the three methods, respectively. Considering the traditional approach (no KM implementation) as the basis, the ratios of Eq. (4) become Eq. (5):

$$\begin{aligned} BII_{\text{trad.}} : BII_{\text{react.KM}} : BII_{\text{IPKMM}} \\ = \frac{[39,800]^{4.26}}{478,656 \text{ s}} : \frac{[39,800]^{7.14}}{233,280 \text{ s}} : \frac{[39,800]^{7.14}}{5 \text{ s}} \\ \approx 10^{13} : 10^{27} : 10^{32} \end{aligned} \quad (5)$$

Using the order of the components in Eq. (5) as indexes, the BII measure for the three periods of KM implementation are 13, 27, and 32 respectively. The BII index provides a simple and meaningful index of competitiveness for the engineering consulting industry to measure their problem-solving capabilities of the firms in providing engineering services.

7. Conclusion and future work

7.1. Conclusions

Engineering consulting is a knowledge intensive industry. Problem solving has been the hard core to almost all kinds of engineering services including proposal preparation, feasibility studies, architectural and engineering designs, procurement, construction supervision, and project management. More and more firms have adopted knowledge management systems as initiatives to enhance their professional services, especially for emergency problem solving. However, the underlying “reactive mode” of the traditional Knowledge Management System (KMS) has hindered further shortening of problem-solving time and resulted in ineffective utilization of the organization’s intellectual assets. This research proposes a novel model, namely the Integrated Proactive Knowledge Management Model (IPKMM) for proactive problem solving. The proposed IPKMM consists of an Enhanced Proactive Problem Solver (EPPS), a Knowledge Value Adding System (KVAS), and an Intellectualization System (IS). The integration of the three subsystems supports the required functionalities of a “proactive mode” of Knowledge Management (KM), which dramatically changes the paradigm of the traditional KM approach to problem-solving in engineering consulting.

The proposed IPKMM does not only provide a useful framework for implementation of proactive knowledge management, but also establishes a mechanism to accumulate the business intelligence in the Intellectual Asset Repository (IAR) that is essential for competing in the market. The knowledge corpuses embedded in reports and documents, which are collected over the years in an engineering consulting firm, are extracted by IS automatically. The extracted knowledge corpuses can nourish IAR and be utilized for solving future emergent problems. Thus, the capability of problem solving in traditional KMS is enhanced.

A Business Intelligence Index (BII) is proposed and defined as an operational index to measure the organization’s competitiveness level in providing their engineering services. With BII, the case engineering consulting firm, China Engineering Consultants, Inc. (CECI), has an index value of 13 before KM implementation. The index increases to 27 after adopting KMS. It is found that the BII further increases to 32 as the IPKMM is implemented. It is concluded that the proposed IPKMM can significantly improve the performance of the professional services for engineering consulting firms, and thus enhance their competitiveness in the service market.

One major limitation of the proposed IPKMM is the requirement of user involvement. In KVAS, COP members have to participate in a questionnaire survey for quantification of KM performance. Also, in Knowledge Categorization Module (KCM) of IS, COP members have to provide the categories of previous Knowledge Cases (KCs) and Lesson-Learned Files (LLFs) for collecting training cases to deduce the knowledge categories of each semantic segment. Another limitation found from the case study is the misclassification problem. Some of the training cases (i.e., LLFs and KCs) were not classified correctly, which can lead to incorrect knowledge categorization in KCM.

7.2. Future work

In the current stage, the Integrated Proactive Knowledge Management System (IPKMS) is installed in China Engineering Consultants, Inc. (CECI). After the setup, valuable information, such as user feedbacks, can be collected for further validating and verifying the proposed method.

As mentioned in Section 4.1, we have observed that most real world knowledge documents do not adopt predefined headings. Authors of the documents usually key in the headings manually, instead of using the Microsoft Office® Word built-in functions. In such cases, the extraction performance deteriorates. It requires a more complex implementation of the Structure Analysis Module (SAM). As the

performance of the IS could be improved when the knowledge documents are well prepared, a document preparation guide for authors has been developed by the research team and provided to the case engineering consulting firm as a facilitating tool for the document preparers. Besides, it is important to review whether documents are well written before submitting them to the system. To this end and to reduce the reviewer's burden, an automatic program should be developed for automatic document checks.

The powerful functionality of proactive knowledge management provided by the proposed IPKMM cannot only be applied to emergency problem solving; it also offers potential benefits to other construction operations as long as knowledge and experiences are incorporated. Future applications of the proposed IPKMM for design, procurement (or bidding), and construction processes will be explored by the research team.

Acknowledgments

The valuable case study data presented in this paper was provided by CECI, Taipei. The authors would like to express sincere appreciation to the involved staffs of the Department of Business and Research and the Department of Information Systems, CECI Engineering Consultants, Inc., Taipei, Taiwan.

Appendix A

List of acronyms

APA	Automatic Problem Answering
APD	Automatic Problem Dispatching
APS	Automatic Problem-solving System
BII	Business Intelligence Index
BQM	Benefit Quantification Module
CBR	Case Based Reasoning
CECI	China Engineering Consultants, Inc.
COP	Communities of Practice
DDS	Decision Support Systems
DM	Data Mining
EMap	Expert Map
EPPS	Enhanced Proactive Problem Solver
FTCM	Figure and Table Categorization Module
FTEM	Figure and Table Extraction Module
IA	Intellectual Asset
IAR	Intellectual Asset Repository
IPKMM	Integrated Proactive Knowledge Management Model
IPKMS	Integrated Proactive Knowledge Management System
IS	Intellectualization System
KC	Knowledge Case
KCB	Knowledge Corpus Base
KCM	Knowledge Categorization Module
K/EMap	Knowledge/Expert Map
KIM	Knowledge Integration Module
KM	Knowledge Management
KMap	Knowledge Map
KMiPS	Knowledge Management integrated Problem-Solver
KMS	Knowledge Management System
KSM	Knowledge-management-activity Surveying Module
KVA	Knowledge Value Adding
KVAQM	Knowledge Value Adding Quantification Module
KVAS	Knowledge Value Adding System
KVASM	Knowledge Value Adding Survey Module
LLF	Lesson-Learned File
LLR	Lesson-Learned Recorder
LLW	Lesson-Learned Wizard
MKO	Multi-dimensional Knowledge Ontology
MPPS	Model of Proactive Problem Solver
PDM	Performance Data-mining Module
PISP	Performance Improvement Strategy Planning

RPS	Reactive Problem-Solving
SAM	Structure Analysis Module
SPM	Strategy Planning Module
SSM	Semantic Segmentation Module
VSM	Vector Space Model

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