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*Research Article*

# Knowledge Management Technologies for Collaborative Intelligence: A Study of Case Company in Korea

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To create wide and deep knowledge flows by providing implicit and explicit knowledge services, organizations have constructed knowledge management systems (KMS). As employees are major knowledge resources in an organization, it is essential to use their collaborative intelligence in KMS, but there has been little research on how the heterogeneous networks of people interact to produce intelligent outcomes. This research suggests a new KM framework that leverages collaborative intelligence techniques, such as collaborative search, collaborative filtering, and social network analysis, as well as conventional knowledge management techniques including smart sensor technology. Finally, this paper reports our experience in a real world KMS development case that applied the framework and suggests challenges of knowledge management learned from this research.

## 1. Introduction

In today's fast-changing global markets, failure or success is no longer tied to the traditional inputs of labor, materials, or capital. What a company knows—and how it leverages that knowledge—has never been more essential for success. Successful knowledge management (KM) can improve an organization's competitive advantages [1] and is the foundation of innovation [2]. Knowledge is thus a significant organizational resource [3]. KM is an integrated strategy of creating, accessing, and supporting knowledge resources to enhance organizational productivity, profitability, and growth [4]. Many KM frameworks and models have been suggested in academia and businesses [5]. The most common components of the frameworks and models consist of a series of processes, such as creation, storage/retrieval, transfer, and application. Conventional KMS have been developed to facilitate these processes.

Conventional KMS have been developed to manage both tacit knowledge and explicit knowledge. Tacit knowledge represents internalized knowledge that is not easily expressed. It is highly personal, hard to formalize, and difficult to communicate with others [6]. Explicit knowledge represents knowledge that the individual holds consciously in mental focus, in a form that can easily be communicated to others. However, it is very difficult to delineate tacit and explicit knowledge and to ensure the success of KMS considering either one of these two aspects. Furthermore, these two types of knowledge have continually been known to interact in the process of knowledge creation and application. Accordingly, it is essential for successful KM frameworks to integrate both implicit and explicit knowledge.

Moreover, people in the organization are essential in successful KM [7]. The spiral model, suggested by [8], addresses that new knowledge always begins with the individual, is transformed into organizational knowledge, and is finally expanded through the organization. It is thus critical for organizations to make personal knowledge available to others. Because collective intelligence techniques can connect people and computers to create the added value, many academics and researchers consider that the collective intelligence can facilitate knowledge management [9–11]. Many practical collective intelligence techniques, such as collaborative filtering, collaborative search, social network, and smart tagging network, have recently been suggested. Little research, however, has employed one of these techniques in constructing KMS (e.g., expert finding using social networks [12]), but they have been studied independently for each technique and do not consider integration of various collective intelligence techniques for implicit and explicit knowledge management. The objective of this research is to combine collective intelligence techniques for better management of both implicit and explicit knowledge.

## 2. Background Studies

*2.1. Technologies for Tacit Knowledge Management.* Tacit knowledge is a crucial source of sustainable competitive advantage because it is difficult for competitors to imitate it. Since organizational tacit knowledge such as know-how, experience, and culture usually resides in members' brains, it is very complex to develop KMS which can help and utilize this type of knowledge with diversity of the expertise and the knowledge needs. Finding experts in the organization and/or over the organization is regarded as one of KMS components that supports tacit knowledge management [13–15]. Yimam-Seid and Kobsa [13] identified two major motivations of expert seeking: (a) as a source of information and (b) as someone who can perform a given organizational or social function.

In order to find experts, it is necessary to construct expert profiles [16, 17] and finding mechanisms. Expertise profiling can be conducted by using manually entered expertise data (e.g., Hewlett-Packard's CONNEX knowledge management system [18]). Manual approach has many shortcomings, including the following four: (1) manual approach is a labor-intensive and expensive task; (2) manual approach depends on the willingness of experts to spend time initially providing a detailed description of their expertise; (3) expertise databases in manual approach easily become outdated; and (4) expertise description of manual approach is usually incomplete and general [13]. In order to overcome these shortcomings, expert profiles can be constructed by leveraging the following resources: author-document-topic graphs [19], taxonomy-based query-dependent schemes [17], contextual factors [20], and linked data on the web [21].

For finding mechanism, much previous research has focused on the information retrieval approaches [22–24]. Social network analysis (SNA) is a promising approach, because SNA provides a rich and systematic means of assessing experts by mapping and analyzing relationships among individuals, groups, and organizations [25]. The value of SNA lies in providing visualization and other features to help people to identify the experts who are not directly connected by their personal network and to manage their networks proactively. Argote and Ingram [26], Cross and Parker [27], and Hansen [28] have revealed the importance of the underlying social network structure for understanding patterns of knowledge sharing. Schwartz and Wood [29] also tried to find people with related interests or expertise by analyzing social networks formed by e-mail communication patterns. Based on PageRank algorithm [30], Kardan et al. [31] suggested an expert finding technique over the public social network by developing an algorithm that identifies the importance of people in a social network.

*2.2. Technologies for Explicit Knowledge Management.* Explicit knowledge is formally articulated or codified information in the form of texts such as written reports, manuals, and analyses. Approximately 80% of corporate information is available in textual data formats [32]. Many knowledge management frameworks define knowledge creation, organization, and sharing as major steps of knowledge management [5]. In explicit knowledge management context, text mining and information retrieval techniques can be used for the process of the framework. While text mining techniques, such as text classification and clustering techniques, are generally used to support explicit knowledge [32–34], text retrieval techniques are used to share explicit knowledge among members.

Information retrieval systems support knowledge management by providing documents in response to a user's information needs. The major task of an information retrieval system is to predict which documents are relevant. Given the information need, the system returns a ranked list consisting of $n$ documents from rank 1 to $n$ in the candidate set. In a conventional information retrieval system, document ranking exploits document characteristics—the contents and relationship between documents—without human efforts. However, document usage can be an important resource for ranking documents. Gou et al. [35] suggest a document ranking method that considers both document contents and the relationship between a searcher and document owners in a social network (named actor similarity). Chidlovskii et al. [36] suggested a ranking method that uses the document-based user and community profiles created by the document collections.

Explicit knowledge management is also supported by the recommender systems. In particular, the recommender systems using the collaborative filtering can suggest relevant knowledge by using explicit and implicit collaboration among humans [37–39]. Collaborative filtering (CF) is the process of filtering information or patterns using techniques involving collaboration among multiple agents, viewpoints, and data sources. To adaptively recommend relevant knowledge, CF is frequently used method in knowledge management [37, 38, 40] and predicts a target knowledge seeker's preferred explicit knowledge based on the opinions of similar users. CF records user behaviors (e.g., browse and search) and recommends documents based on the past behaviors of other users when they performed similar behavior patterns. CF algorithms are often distinguished by whether they operate over implicit versus explicit rates. Explicit rating refers to a user consciously expressing preference to indicate the quality of specific content, usually on a discrete numerical scale. Poston and Speier [38] found that content ratings have a strong influence on KMS search and evaluation processes, which in turn affects decision performance. Implicit rating refers to interpreting user behavior to impute a preference. Implicit votes can be based on browsing data and other types of information access patterns. CF technology ranges from simple nearest neighbor methods based on a combination of the scores rated by nearest neighbors [41] to more complex machine learning algorithms such as Bayesian network model [42] and linear algebra-based methods [43]. One of the popular model-based algorithms is the clustering techniques for collaborative filtering [44, 45] which identify groups of users who appear to have similar preferences. Once the clusters are created, predictions for an individual can be made by averaging the opinions of the other users in that cluster.

One technology that can automatically enable enterprise collaborative knowledge sharing, creation, and application between a production sector and business office sector is smart tagging technologies which can be also called as radio frequency identification (RFID). Previously, smart tagging technologies implementation took place within a company with the objective to simply automate the supply chain process [46] and logistic processes [47]. RFID is proved to be a practical tool to monitor and reflect production and logistics processes and activities on a real-time basis [47]. However, very few software products were designed for the integration of the RFID data with those for enterprise wide knowledge management application. Thus, the employment of smart sensor technology in operational facilities can create new types of knowledge, leading to a more precise representation of the physical operation environment. Employees can benefit from integrating real-time RFID information with knowledge management system in gaining higher domain knowledge specificity by sharing seamless information through automated and secure interorganizational network links. Similarly, Chow et al. (2007) proposed a dynamic logistic process knowledge-based system named LPKMS which describes the real-time status of process environments through diagnosing multiple real-time data and information sources and also delivers logistic process procedures (explicit knowledge) and logistic process logic (tacit knowledge) to employees who are performing various logistics processes in real time. Such RFID enabled KMS can provide information of real-time production and logistic progress status, thereby helping knowledge seekers (e.g., from marketing or financial sector) to apply this operational knowledge in making quicker, more informed business decisions to achieve their objectives [48].

## 3. Collaborative Knowledge Management Framework

Many knowledge management frameworks have been suggested by many researchers [5]. However, most of these frameworks have focused on knowledge itself rather than people who should collaborate with one another. For example, the spiral model proposed by [8, 49] explains the dynamic conversion between tacit and explicit knowledge. In the spiral model, new knowledge always begins with the individual, is transformed into organizational knowledge, and is finally expanded through the organization. It is thus critical for an organization to make personal knowledge available to other members in the organization. It takes place continuously and at all levels of the organization. Through these interactions an organization creates a knowledge process, called knowledge conversion. Nonaka et al. [8] propose four modes of knowledge conversion: socialization (from tacit knowledge to tacit knowledge), externalization (from tacit knowledge to explicit knowledge), combination (from explicit knowledge to explicit knowledge), and internalization (from explicit knowledge to tacit knowledge). These four modes of knowledge conversion form the SECI process. Knowledge created through this spiral process can trigger a new spiral of knowledge creation, expanding horizontally and vertically across organizations.

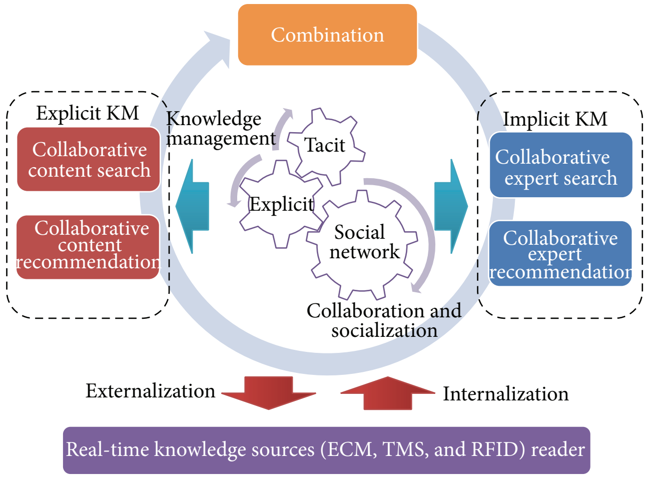

Figure 1: Collaborative knowledge management framework.

However, most of these frameworks do not integrate knowledge management with collaboration [5, 37]. The importance of the convergence of collaboration and knowledge management is significantly increased as many collaborative technologies have recently been developed. Some researchers provide frameworks for this approach including [50–53].

Our collaborative knowledge management (CKM) framework is illustrated in Figure 1. CKMS aims to manage both tacit and explicit knowledge using collaboration technologies. CKMS internalizes real-time knowledge from various internal sources (e.g., ECM, TMS, and RFID reader) and external sources (web, news, and blogs). The members externalize their knowledge by creating documents based on available tacit and explicit knowledge. Knowledge obtained from knowledge sources is socialized via social networks within an organization. In order to support explicit knowledge management, CKM supports easy content finding mechanisms in response to individual needs for information. On top of the conventional content search, CKM ranks the contents based on the collaborative reflecting collaboration factor. In addition to collaborative content search, CKM supports collaborative content recommendation, exploiting collaborative contributions of organization members. CKM also supports implicit knowledge management by supporting expert findings in an organization using social network analysis and supporting search and recommendation of experts. Finally, CKM supports dynamic combinations of knowledge management components.

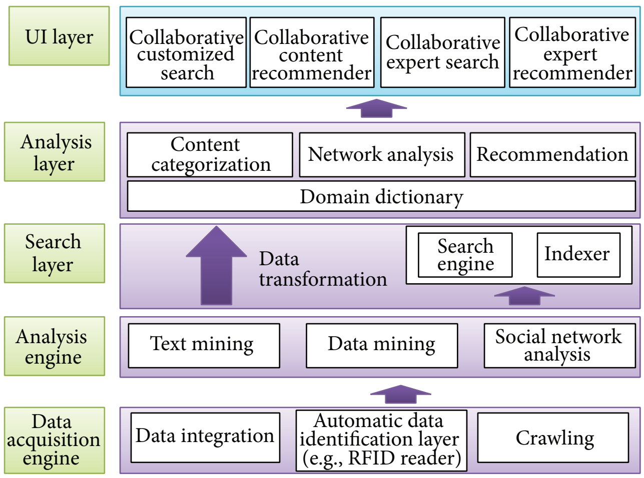


Figure 2: Collaborative KMS architecture.

## 4. Case Company-Collaborative KMS

The case company was founded in the 1960s and it has become world leading steel company as a large conglomerate having 22 subsidiaries across various industries including plant construction, trade, ICT consulting, and energy and chemistry. The case company has been well known for its technological innovation in Korea. For example, the company established an integrated digital system in 1990s through fundamental business transformation, reorganizing all work processes from purchase and production to sales. Based on the CKM framework as we suggested before, the KMS, called collaborative KMS (CKMS), was implemented across all family companies. The CKMS aims to support and enhance the organizational processes of knowledge creation, storage/retrieval, transfer, and application, through using various collaborative technologies, including collaborative document ranking, collaborative recommendation, and social networks. The CKMS was adopted by over 10,000 people and is used to search for the expertise and social network of every employee of the conglomerate.

*4.1. Architecture.* As shown in Figure 2, the CKMS consists of the five components: data acquisition engine, text analysis engine, and three layers of search, analysis, and user interface. Each component performs the following roles.

*(i) Data Acquisition Engine*. Data for the CKMS are collected from the internal (e.g., ECM, TMS, RFID reader, etc.) and external knowledge sources (e.g., news, blogs, etc.). Data acquisition engines incorporate with data integration which is to combine data from different sources; automatic data receiver and the crawler collect data from the web resources. RFID technology was combined with the procurement process of the company in order to track documents as well as materials related to the purchased materials. RFID tags were placed on the purchased materials and were tracked from the suppliers to the company.

*(ii) Data Analysis Engine*. The CKMS employs data analysis engines which can be used to analyze input data. Data analysis engines perform text mining, data mining, and social network analysis.

*(iii) Search Layer*. By indexing collected data, the CKMS prepares them to be efficiently searched and retrieved.

*(iv) Contents Analysis Layer*. Contents categorizer automatically classifies documents into each category based on predefined category rules and conceptual definition and automated tagger generates annotating tags for documents (texts). Network analyzer analyzes data in order to construct social networks. Social networks are created by employees and by keywords in the text. Recommender analyses expert profiles and text data create recommendation databases.

*(v) User Interface Layer*. To support collaborative knowledge management, CKMS provides users with various services: collaborative customized search, collaborative recommendation, collaborative expert search and collaborative expert recommendation, and collaborator network.

*4.2. Convergence of Knowledge Management with Collaboration.* Figure 3 illustrates how to combine the different components for the collaborative knowledge management. Task type classification identifies task types and their explanatory keywords. Once the task types are successfully identified in the classification, the employee profile classification and the contents classification processes are conducted to classify employees and contents into task types. Based on the employee profile classification, each employee's expertise areas are identified and they are used to support expert search. Contents are dynamically recommended to the employees after clustering expertise areas, where the clustered expertise areas are used as information needs. Content classification is used in many ways. First, the content classification is used to identify the interest area of the users. Combined with expert area and content usage index, the interest area of the user is used to provide customized search service. Content classification is also used to construct social network diagrams for the employees. Three persons, including the responsible person, the accountable person, and the informed person, are involved and indicated in each document. Social networks are also used to provide expert recommendation.

*4.3. Task and Profile Classification.* In order to extract keywords that describe tasks, SEMMA (sample, explore, modify, model, assess), a logical organization of the functional tool set of SAS Enterprise Miner for carrying out the core tasks of data mining was employed for this project [54]. The SEMMA process offers an easy-to-understand process to allow organized and adequate development and maintenance of data mining projects.

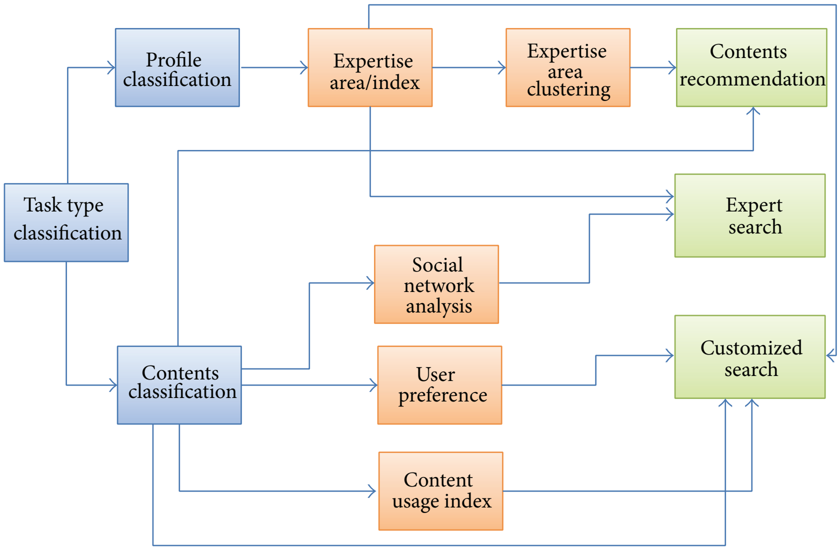


Figure 3: Processes for collaborative knowledge management system.

Based on SEMMA, we conducted task classification as follows.

*Sample*. This stage chooses sample data (contents and profiles) from a representative department for specific task types by extracting a portion of a large data set, which is big enough to contain the significant information, yet small enough to manipulate quickly.

*Explore*. This stage explores the sample data using text mining techniques in order to find unanticipated trends and anomalies and to gain broad understanding and ideas. From this process we can get keywords for task type classification. Keyword appropriateness is evaluated using the following formula:

$$U_w = \frac{DP_w}{DP}, \quad (1)$$

where $w$ is a keyword selected by text processing algorithm, $DP_w$ is the number of documents and profiles that contains keyword w and $DP$ is the number of documents and profiles that contains all keywords.

*Modify*. This stage modifies the data by creating, selecting, and transforming the variables to focus the model selection process. At this stage, a set of keywords is defined through a keyword standardization process and a keyword grouping process.

*Model*. This stage models the data by allowing the system to perform task classification automatically that reliably predicts a desired outcome and to explore new keywords by using text mining techniques.

*Assess*. This stage assesses the data by evaluating the usefulness and reliability of the task type classification and estimates how well it performs.

Based on SEMMA, our task classification was conducted as described in Figure 4. At the beginning, the employee provides his/her profile such as job title, career, contents, and job results, and the profiles are updated every six months. Using profile attributes, the employees' profiles are classified and expertise areas and index are identified. The expertise index is only based on the length of the career in a specific expertise area. Each employee's expertise index is calculated using statistical distribution of the experts in an expertise area.

*4.4. Contents Recommendation Process for Collaborative KMS.* Basic contents recommendation is similar to the collaborative filtering, which recommends items using similar users' preferences. The recommendation process starts with defining the similar employees who seem to have similar preferences. In this research, the similar users are defined by the employees who belong to the same department and expertise areas obtained from the profile classification. In order to define expertise areas, we used clustering techniques to classify employees' profiles. Initially, the CKMS creates fifty clusters of profiles and each cluster is evaluated by the experts in the company. Twenty-eight clusters were selected as the final clusters. After defining the similar employees, the system retrieves documents that were created by the similar users within last three months. For the given document x and y, the support and confidence are calculated as follows:

(i) support = $(V_{d_x}/V_c) \times 100$, where $V_d$ is the number of viewers who viewed document $x$ in the cluster $c$ and $V_c$ is the number of viewers who viewed documents of the cluster $c$; and

(ii) confidence = $(V_{d_{x,y}}/V_{d_x}) \times 100$, where $V_{d_{x,y}}$ is the number of viewers who viewed document $x$ and $y$ and $V_{d_x}$ is the number of viewers who viewed document $x$.

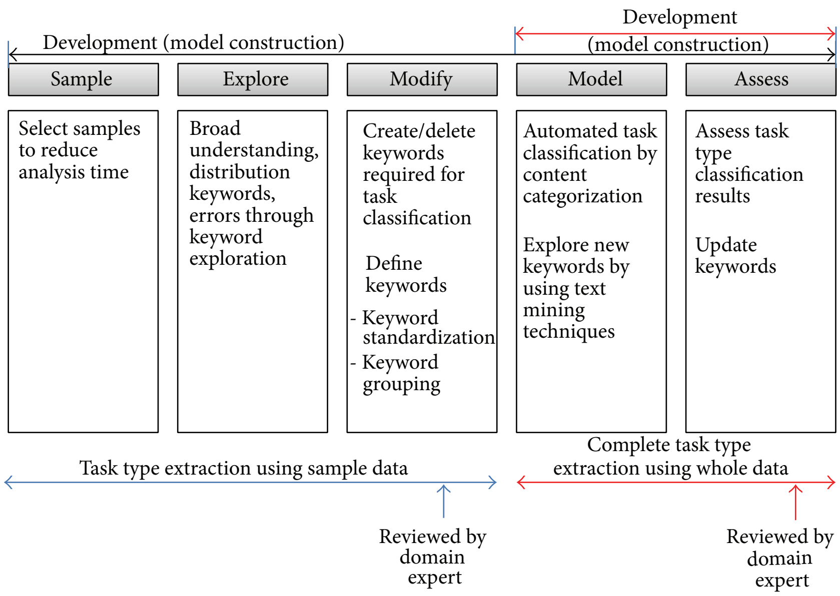


Figure 4: Task type classification.

The support and confidence are used to rank the retrieved documents and listed first for the documents that have not been viewed by users.

*4.5. Document Ranking Based on Content Usage Index.* Content usage index (CUI) is generated by using average and distribution of expert and nonexpert document viewers. CUI is used to rank a list of retrieved documents by analyzing contents usage by document viewers. Detailed content usage index is calculated as follows.

(1) A number of expert and nonexpert document viewers are calculated for each document.

(2) Average distribution values of a number of viewers for each analyzing period (1 month, 3 months, and 1 year) are calculated.

(3) 80% of accumulated standardized normal distribution is acknowledged for expert document viewers (T1) and only 20% of standardized normal distribution is acknowledged for nonexpert document viewers (T2):

Usage index (Ui) for a specific analyzing period ($i$) = 0.8 $*$ T1 + 0.2 $*$ T2 ($i$ = 1 month, 3 months, 1 year).

(4) Finally, different weight values are used for each analyzing period:

Contents usage index (CUI) = 0.6 $*$ U (1 month) + 0.3 $*$ U (3 months) + 0.1 $*$ U (1 year).

*4.6. Social Network Analysis for Collaborative KMS.* SNA contains a rich set of data about the person seeking knowledge about those who may have access to the knowledge. SNA may enable individuals to rapidly locate the individual who has the knowledge that might help them solve the current problem. The primary content of the system is a set of expert profiles containing a directory of the backgrounds, skills, and experience years in a specific area. Such metadata (knowledge about where the knowledge resides) is often proven to be as important as the original knowledge itself [55]. The CKMS derives such metadata about work experience in a specific expertise area, by extracting the information and by deriving artificial intelligence algorithms from existing sources. We extracted keywords from the documents created within certain time period (e.g., one month). Then we calculated the relationship strength (confidence) of two keywords by computing confidence value. Based on the confidence value, top $N$ related keywords are identified as a social network of each keyword. We have identified the following two types of social networks. Through the networks we can find an expert, the person whose expertise is defined by what they know and by the person who is central in a network.

*(i) People-Based Social Network.* We identify people-based social network by analyzing document circulation information. There are three persons involved in creating a document: a responsible person who initially creates the document, an accountable person who signed the document, and an informed person who was reported by the responsible person or the accountable person. Using this information a social network can be created for each person. People-based SNA is identified by the transactions between document creator and document readers. The strength of the links is calculated by the number of downloads.

*(ii) Expertise Area-Based Social Network.* We identify expertise area-based social network by analyzing experts for each expertise area. If a person belongs to an expertise area, a social

network is constructed for all employees whose expertise area is the same as the person.

Network strength is based on the volume of contents shared between the nodes (employees). The network also shows the keyword that represents two nodes as well as organizational relationships between employees. In addition, the CKMS also provides the networks that analyze the relationships between relevant keywords which frequently coincide together. Through the network strength within keyword networks, users can catch a flow of specific knowledge area.

The CKMS uses these above social network analysis services as follows. If an input keyword is submitted by a user, a set of experts for the keyword entered is displayed. Once the experts are identified, KMS suggests various types of social network including expert centered social network, expertise-based social networks, and keyword centered networks on request of the user.

## 5. Discussion

*5.1. Validation.* Existing KMS have employed one of the collaborative techniques without consideration of continuous interaction between explicit and tacit knowledge in knowledge conversion process. However, the CKMS integrates various collective techniques for explicit and implicit knowledge management by supporting aspects of knowledge conversion: (1) socialization (by providing links between users who search tacit knowledge and experts who have that knowledge through a social network-based expert recommendation system), (2) combination (by merging, categorizing, reclassifying, and synthesizing existing explicit knowledge through a collaborative filtering recommendation system (CFRS) and customized content search (CCS)), and (3) internalization (through CFRS and CCS with great exposure to greater amounts of knowledge sources including online organizational information from RFID, ECM, TMS, blogs, search logs, and external sources both horizontally and vertically). As the level of information exposure increases, the internalization mode of knowledge conversion, wherein individuals make observations and interpretations of information that result in new individual tacit knowledge, can be increased. Finally, (4) externalization mode of knowledge conversion can be promoted by encouraging experts to create new documents based on knowledge collaboration and socialization activities of the system and upload them to increase their ranking of expertise and overall expert reputation within the company.

The previous prototypes of KBS and EFS, which support socialization processes between knowledge seekers and experts by introducing the concept of knowledge broker, lack the supporting conversion activities between tacit knowledge and explicit knowledge. PKMSS, which was developed for knowledge sharing for schools, tried to consider every aspect of knowledge conversion process but its technologies which were adapted to the system were limited to promote collaboration intelligence between teachers. The comparison between the similar systems and CKMS is presented in Table 1.

*5.2. Operational Knowledge Management with Smart Sensor Network.* Our project was successful since a KMS that supports collaborative intelligence has been successfully implemented within the company. Thus, this project mainly focused on knowledge created in an office environment. However, as the company is one of largest manufacturers in Korea, real-time operational knowledge coming from various operation and logistics activities is also very important for KMS. Knowledge within logistics and production is a collective memory of past experience and rules that determine how resources are utilized to make and deliver products and services. However, this type of knowledge is often not shared with other distributed parties, and knowledge creation, sharing, and application activities of such operational knowledge types are very limited as they only rely on performance and regular reports that are amplified and codified by employees rather than real-time information that was automatically generated across production and chain processes. Brown and Duguid [56] claimed that the vast majority of knowledge encompassed in a successful business practice is uncodified and held tacitly in the minds of those employees performing the task. In order to enable successful collaborative knowledge management, both explicit (e.g., real-time production status, history, and performance) and tacit (e.g., best practice and experience) knowledge should coexist together and be accessible in real time. Data collected from the sensor networks in production and logistic operations are important sources for knowledge management in the company. Modern plants and logistic systems are equipped with various sensors and alarms and experts in these workplaces use the data to manage production and logistic operations efficiently. Explicit and implicit knowledge are closely related to these data sources. Large volumes of these data are usually created and it would be very difficult to manage them without appropriate data analysis and mining support. In particular, it is essential to respond to the events in the production and logistic environments and thus the data analysis should be conducted in real time with a large volume of data. One of the major challenges for the future KMS is to combine KM approaches suggested in this research with the sensor network and data analysis techniques. There are lots of researches on the sensor network and sensor data analysis, but they are not integrated with the corporate knowledge management efforts. By adopting RFID technology into knowledge-based system it is possible to eliminate non-value-added process and other processes will be operated in productive ways.

## 6. Conclusion

Knowledge management systems supporting tacit and explicit knowledge and dynamic conversion between them are emerging as a powerful source of competitive advantage. However, the general recognition of the importance of such systems seems to be accompanied by a technology induced drive to implement systems with inadequate consideration of the fundamental knowledge management process that the KMS should support. As noted by Ackerman et al. [57],

Table 1: Comparison between the similar systems with CKMS.

| System | Authors | Knowledge conversion process | | | | Collaborative technologies | | |
|---|---|---|---|---|---|---|---|---|
| | | Socialization | Combination | Internalization | Externalization | Collaborative document ranking | Collaborative recommendation | Social network |
| KBS | Kim and Andrew Yang [53] | O | X | X | △ | X | X | O |
| EFS | Lin [24] | O | X | X | X | X | X | O |
| PKMSS | Lee et al. [58] | △ | △ | △ | △ | X | △ | X |
| CKMS | This study | O | O | O | △ | O | O | O |

the goal of knowledge management systems has to be beyond the immediate knowledge needed by organizational members. For successful KMS fostering the collaboration intelligence that drives mutual company growth, we focused on knowledge conversion processes between implicit and explicit knowledge created by experts in various knowledge domains in organizations. This paper contributes to the stream of research on knowledge management by proposing an inductively developed framework fostering collaborative intelligence. Particularly, the integration of RFID technology for the purposes of knowledge management is one of the contributions of this research. The CKM framework provides a means to the exploration of issues related to KMS for tacit and explicit knowledge and unifying collaborative technologies supporting different modes of knowledge conversion.

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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