Knowledge Management Using Recommender Systems

S. S. Sandhu and B. K. Tripathy

Abstract Knowledge is defined as the practical or theoretical comprehension of a subject. It refers to the skills, information, and facts acquired over time through education and/or experience. Knowledge management plays a vital role in the industry today. Knowledge that cannot be shared or communicated with others is mostly redundant and becomes actionable and useful only when shared. Knowledge management refers to a set of processes developed specifically for the purpose of creating, storing, disseminating, and applying knowledge. The idea here is to give an organization the capability to learn from its environment and to incorporate the acquired knowledge into its business processes so as to streamline them and increase their efficiency. With the amount of data/information increasing exponentially, discerning what information is relevant becomes tougher by the day and as a result, knowledge management systems are gaining importance. Recommender systems are a subcategory of information filtering systems. These seek to predict the probability of a user preferring a particular item out of a given set of items. To aid in the knowledge retrieval and dissemination processes of knowledge management systems, the use of intelligent techniques is on the rise. Recommender systems form one such category of intelligent techniques. This chapter presents an overview of the different works done to incorporate recommender systems into the domain of knowledge management. Applications in the scientific, engineering, and industrial knowledge management contexts have been discussed.

S. S. Sandhu (✉) · B. K. Tripathy
School of Computing Science and Engineering, VIT University,
Vellore 632014, Tamil Nadu, India
e-mail: sabhijiit@gmail.com

B. K. Tripathy
e-mail: tripathybk@vit.ac.in

S. Margret Anouncia and U. K. Wiil (eds.), *Knowledge Computing and its Applications*, https://doi.org/10.1007/978-981-10-8258-0_9

1 Introduction

The following passages introduce certain keywords concerning the topic of discussion.

1.1 Data, Information, and Knowledge

To understand the term “knowledge,” it is first important to also understand the terms “data” and “information,” and how they all relate to and differ from each other. Laudon and Laudon [1] define data as “a flow of events or transactions captured by an organizations system that by itself is useful for transacting but little else.” In other words, data is a collection of facts or figures which can be used for the purpose of making inferences. It is the raw material from which information is obtained. According to Robert M. Losee’s “Discipline Independent Definition of Information” [2], information can be envisaged as the “Value attached or instantiated to a characteristic or variable returned by a function or produced by a process.” It is the data that, within a framework, has been recorded, classified organized into categories of understanding and related, or interpreted within a framework so that meaning emerges. Lastly, knowledge is interpreting the information available at hand to find patterns, rules, and contexts (Fig. 1).

Knowledge can be classified using many different labels. It can be a cognitive or even a physiological event, that might have an intangible form, taking place inside peoples’ heads, or is also available in many tangible forms such as those that are either shared during lectures or stored in records and libraries. Firms also store it in the form of employee know-how and business processes. Knowledge is of two types: One is the tacit knowledge which is undocumented and resides in the minds of employees. The other is explicit knowledge which refers to the documented part. Knowledge is generally believed to be located somewhere in specific business

Fig. 1 DIKW pyramid (also known as the “knowledge hierarchy,” is used to represent the functional and structural relationships between data, information, knowledge, and wisdom. It defines information in terms of data and knowledge in terms of information [54])

processes or in human brains. It can also reside in unstructured or structured documents, in voice mail, or e-mail, as well as in graphics. Knowledge is "sticky" in that it is rather slow and very difficult to transfer knowledge from one person to the other. This is because most knowledge is not universally applicable, having been obtained from information and data for a particular process. Finally, knowledge has both situational and contextual characteristics [1, 3].

1.2 Concept of Knowledge Management

Alavi and Leidner [4] present the various implications and the different perspectives of knowledge that have on knowledge management (Table 1).

Knowledge management refers to the use of certain tools, methods, and procedures to efficiently manage the resources and information within institutions such as commercial organizations. Quintas et al. [5] state that "knowledge management is a process of continually managing knowledge of all kinds and requires a company-wide strategy which comprises policy, implementation, monitoring, and evaluation." They further add that "Such a policy should ensure that knowledge is available when and where needed and can be acquired from external as well as internal sources." The knowledge management process has five steps [1].

1. Information systems activities
2. Knowledge management systems
3. Organizational and management tasks
4. Assessment and evaluation
5. Acquiring data and information.

Table 1 Different perspectives of knowledge and their implications for knowledge management

Perspective	Implication on KM
Knowledge from data and information	KM is focused on granting individuals exposure to information that might be potentially useful as well as smoothening the information assimilation process
Knowledge in terms of "state of mind"	KM attempts to enhance the learning and comprehension of an individual by providing information
Knowledge as an "object"	KM's primary concern here is to build and manage knowledge stocks
Knowledge as a "process"	KM focuses on the flow of knowledge and the processes of creation, distribution, and sharing of knowledge
Knowledge in terms of "access to information"	The key KM issue here is to organize the processes of accessing and retrieving content
Knowledge in terms of "capability"	KM is concerned with understanding strategic know-how and building core competencies

This table has been referred from [4]

Knowledge management is focused on creating/extracting value from organizations intangible assets. The driving force behind knowledge management is the aim to create a process that can value a firm/organization's intangible property to allow for its effective usage. The idea is to provide an environment that is conducive to sharing knowledge as opposed to simply keeping it to oneself [6].

1.3 Knowledge Management Systems

Knowledge management systems are a collection of business processes devised to allow an organization to create, store, share, and use knowledge. These collections are IT-based systems that are used to improve the capability of organizations to learn/gain information from their environment and incorporate this acquired information into their business processes.

Knowledge management systems are of three major types:

- Enterprise-wide knowledge management systems
- Knowledge work systems (KWS)
- Intelligent techniques.

Davenport et al. in "Successful knowledge management projects" [7] talk about the objectives of knowledge management projects along with the conditions to be met and the factors that come into play for a knowledge management project to be counted as a success.

Gold et al. in "Knowledge management: An organizational capabilities perspective" [8] present their findings from a research conducted that examines from a perspective of an organizations capabilities, the issue of effective knowledge management.

Numerous knowledge management frameworks have been devised over the years. Some are given below along with their descriptions.

- By Van Heijst et al. [9]: Develop, Consolidate, Distribute, Combine.
- By The National Technical University of Athens, Greece [10]: Get context, Organize knowledge according to knowledge management goals, Strategize development and distribution, Culture.
- By American Management Systems [11]: Find knowledge, Organize it and Share.
- By Arthur Andersen Consulting [12]: Evaluate the target/problem, Define what the role of knowledge is and Create a knowledge strategy for the specified target, Identify technologies and processes needed for implementation, and lastly, Implement feedback mechanisms.
- By Dataware technologies [13]: Identify problem, Prepare for the change, Create a KM team, Perform the audit and analysis of knowledge, Define the main features of proposed solution, Implement the building blocks, and finally Link the knowledge to people.

- By Ernst and Young [14]: Generate knowledge, Represent it, Codify it and finally, Application of knowledge.
- By Holsapple and Joshi [15]: Acquire knowledge, Select required knowledge, Asses, Target and Deposit knowledge, Use it, Generate knowledge, Externalize knowledge.
- By Liebowitz [6]: Transform the information into knowledge, then Identify and Verify knowledge, Capture and Secure it, Organize it, Retrieve and Apply it, Combine it, Learn knowledge, Create knowledge (Loop from step 3), Sell it.
- By Marquardt [16]: Knowledge Acquisition, Creation, Transfer and Utilization and Storage.
- By O'Dell [17]: Identify, Collect, Adapt, Organize, Apply, Share, and Create knowledge.
- By Ruggles [18]: Create, Acquire, Synthesize, Fuse and Adapt knowledge, Capture and Represent knowledge, Transfer it.
- By The Mutual Group [19]: Gather information, Learn/Gain knowledge, Transfer it and Act accordingly.
- By American Productivity and Quality Center [20]: Find knowledge, Filter and Format it, Forward it to relevant people and Get feedback.
- By Van der Spek and Spijkervet [21]: Develop new knowledge, Secure it along with existing knowledge, Distribute these, and Combine all available knowledge.
- By Wielinga et al. [22]: Inventory, Represent and Classify knowledge, Create models for knowledge development and knowledge results and resources, Combine, Consolidate, Integrate, Develop and Distribute knowledge.
- By Wiig [23]: Create and Source knowledge, Compile and Transform it, Disseminate knowledge and Conduct Value Realization.
- By Knowledge Associates [24]: Acquire, Develop, Retain, and Share knowledge.
- By The Knowledge Research Institute [25]: Leverage the already existing knowledge followed by Creating new Knowledge and Capturing and Storing it, then Organize and Transform it and finally Deploy the knowledge.

1.4 Recommender Systems

To understand what "Recommender Systems" are, we first take a look at the term "Information Filtering System." Information filtering systems are systems that aim to expose users to only that information that is useful/relevant to them. They remove extraneous data from incoming streams of data using computerized or (semi) automated methods.

Recommender systems are a class of information filtering systems that seek to predict the probability of a user choosing an item by assigning ratings. They identify recommendations autonomously for individuals based on their previous search (and purchase) history as well as based on other people's behavior. These recommendations are made to ease the decision-making process such as what song to listen to, what video to watch, what product to buy, or what news to read. Recommender systems serve to increase the interaction between the user and UI so as to provide a richer experience [26, 27].

Recommender systems are mainly aimed at people that lack enough experience or proficiency to navigate through the potentially massive amount of results a Web site, for example, might return for a given search string. Recommendations are both of personal, which are usually unique to each individual, and generalized nature, which are simpler to generate and are typically along the likes of top ten movies/songs of all time, etc [28].

Ricci et al., in the Recommender Systems Handbook [28], put forth several reasons why service providers might choose to employ the technology:

- *To increase the number of items sold.* As the recommended item has a good chance of fitting the user's needs, this goal is likely to be achieved.
- *To sell more diverse items.* Less popular material from a user's preferred genre/choice can also be advertised to the same using recommender systems.
- *To increase customer satisfaction.* With the presence of a properly designed UI, customer experience can be improved and this along with interesting and relevant recommendations serves to increase customer satisfaction.
- *To increase customer fidelity.* Increased customer satisfaction directly translates to increased customer fidelity. The more time a user spends on the site, the more refined their preference information becomes. This allows the recommendations to become highly customized to match preferences of the user.
- *To better understand what the user wants.* This important function of recommender systems can be leveraged to many other applications as well. Knowledge of user preferences can be reused for other purposes rather than just recommending.

Herlocker et al. [29] put forth eleven "End-User goals and tasks" that recommender systems help to achieve.

- *Annotation in context*: Certain specific existing content is emphasized upon based on the user's preference history.
- *Find all good items*: This recommends each, every item that can fulfill the requirement of user. Here, it is not enough to only recommend some good items.
- *Find some good items*: Here, only some items are recommended according to their rankings which show how likely it is for the user to use them.
- *Just browsing*: This is when the user is going through the product catalog without any intention of making a purchase. The recommender system should suggest products that would most likely fall within the user's area of interest.
- *Improve user profile*: This is a necessary task to achieve personalized recommendations. The user should be capable of providing information about his or her likes and dislikes to the recommender system.
- *Expressing self*: Users should be allowed to express their satisfaction or lack of it on the Web site. Though not a part of the recommendation process directly, it counts in terms of customer satisfaction.

- *Helping others*: Like the previous point, this is also to do with ratings and feedback as some users are happy to contribute information for the benefit of others.
- *Influence others*: In online recommender systems, there might be some malicious users that would like to influence others into purchasing some products.
- *Find credible recommender*: Some functionality can be offered to allow the user to test the quality of recommendation of the system.
- *Recommend a sequence*: Here, recommending a series of items, like a movie or TV series, a discography, or a collection of books is the primary goal.
- *Recommend a bundle*: Here, a bundle of goods that fit well as a group are recommended, for example, a tourism voucher may comprise a number of travel destinations located close by.

There are three basic approaches that are adopted to design most recommender systems [30]. Two of the more common one's, Collaborative filtering and Content-based filtering, have been discussed here.

Collaborative filtering models recommendations based on a user's prior behavior. These recommendations can be solely based on an individual's behavior or can also incorporate from the behavior of other users with similar traits and to much better effect. For example, an online music player uses a collaborative recommender system to suggest new songs. How it does this is, it uses information from the myriad subscribers who regularly listen to songs and groups the users together based on their listening preferences. For example, subscribers listening to mostly similar genres are grouped together. From their information, a list of most popular songs/artists/genres is then prepared and to any particular user in that group, the music player recommends the most popular songs/artists/genres that he or she neither listens to nor follows. Refer to Fig. 2 for a pictorial representation of the collaborative filtering logic.

Content-based filtering methods compare the item's description with a profile of the user's preferences to decide whether to recommend that particular item or not. Here, items are described using keywords and the profile of an user is built

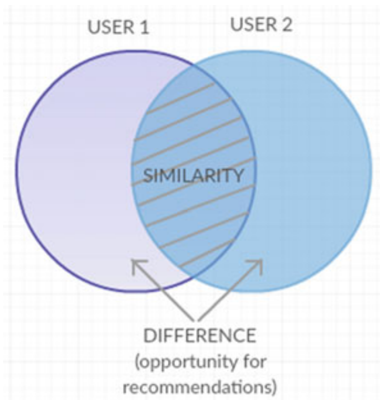


Fig. 2 A sparse representation of the collaborative filtering approach

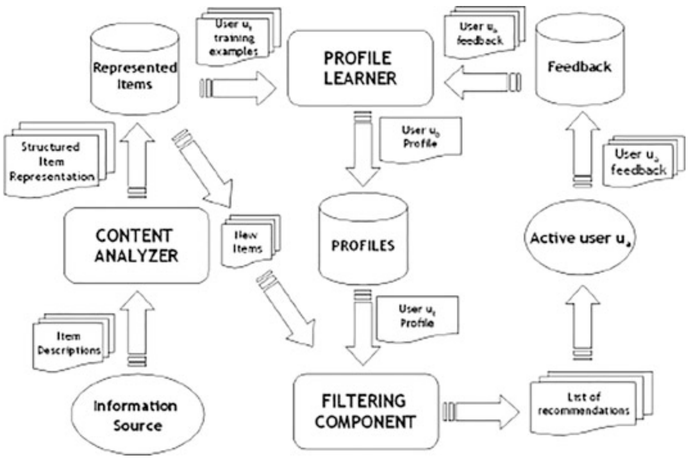


Fig. 3 Architecture for a content-based filtering recommender system (Figure was originally proposed by Felfernig et al. [30])

using selected keywords that are indicative of the user's preference history. In other words, recommendations here are of items that either belong to preference history of the user or are similar to his current search interest. Content-based filtering involves comparing various candidate items with the user's previously rated items, and the best matching items are returned. Refer to Fig. 3.

As stated before, recommender systems assign ratings to items to predict their chances of being selected by the user. There are several different data mining techniques that can be used to assign these ratings. The data mining process has, broadly speaking, three main steps. *Data preprocessing*, followed by *data analysis,* and lastly *result interpretation*.

Data Preprocessing involves processes to "prepare" the data in order to make it suitable for application of the machine learning techniques in the data analysis step. The major tasks in the data preprocessing stage are data cleaning, data integration, data reduction, data transformation, and data discretization. Data preprocessing is important as it improves the accuracy of the input data, makes sure it's complete and consistent, and enhances its believability and interpretability. The major tasks here are as follows [31]:

- filling in missing values, smoothening the noisy data, and removing outliers;
- integrating data across multiple files and databases;
- data compression and dimensionality reduction;
- data normalization.

Data Analysis in recommender systems is concerned with classifying the items into different labels (classes). This involves mapping each element based on its characteristic features to an appropriate label. For example, a book recommender system might classify a book as popular or unpopular based on the number of reads it has.

While there are various classifiers out there, we will limit our discussion to supervised and unsupervised classification. Supervised classification is when both the input and the output variables are known, and the algorithm is concerned with learning the mapping from the input to the output. The goal is to get an approximate mapping function such that for any new input data, the output can be correctly predicted. Since the outputs here are already known, the process is known as supervised learning. Unsupervised classification occurs when only the input data is given, and corresponding outputs are unknown. The aim of unsupervised learning is to gain intuition about the underlying structure or distribution of the data in order to learn more about it. Unsupervised learning algorithms are so called because they do not have any correct answers, and there is no supervision of the results obtained. The algorithms are expected to model or represent the data unassisted and on their own.

Some supervised and unsupervised classification algorithms are as follows:

- *Nearest neighbors algorithms* are supervised learning algorithms that find the most closely related data points for the point to be classified and assign its class label on the basis of those "nearest neighbors." The idea is to assign a point to whatever class label is predominant in the neighborhood of the area where it lies.
- *Decision trees* are supervised learning algorithms whose goal is to correctly predict the value of the target variable given several input variables. These are of two types, classification trees where the predicted outcome is the class label or regression trees, where the predicted outcome is a real number.
- *Rule-based classifiers* are supervised learning algorithms that work using the "if…then…else" construct. Here, the condition or rule antecedent is an expression made by attribute conjunctions. The rule consequent is an outcome or classification that can either be positive or negative.
- *Bayesian classifiers* are supervised learning algorithms that use a probabilistic framework for the classification process. They make use of the Bayes theorem and conditional probability. Here, the uncertainty in relationships is modeled using probability. Each attribute and class label is considered as a random variable for the Bayesian classifiers problem. They seek to predict the correct label by finding the class that gives maximum posterior probability for a given data.
- *Artificial neural networks* are supervised learning algorithms that seek to model the structure of the biological brain. They are made up of an assembly of interconnected nodes called neurons with weighted links. The neurons are analogous to the brain's axons. Layers and layers of these neurons form a network that after being trained with an adequate amount of data can learn the classification problems. These are designed to perform nonlinear classification task as well as stay robust in the face of partial system failure.
- *Support vector machines* are supervised learning algorithms that are discriminative classifiers that are defined by a separating hyperplane. That is, the input data is separated in such a way that the optimal hyperplane maximizes the

margin between itself and the data points. The rationale behind support vector machines is that if the margin is maximized, future misclassification of unknown data becomes less likely.

- *K-Means* is an unsupervised learning algorithm that seeks to partition a data set into k contiguous clusters in such a way that the within-cluster sum of squares is minimized. It works by randomly initializing the cluster centroids, assigning points to the closest centroid and then repeatedly revising the centroid allocation till the sum-of-squares metric is not minimized. This ensures high intra-cluster but low inter-cluster similarity.
- *Association rule mining* is another unsupervised learning algorithm that finds rules for predicting occurence of an item in a transaction based on other items of the same transaction. Association rules are also "if…then" construct based that generate relationships between seemingly unrelated items/data. To create the rules, the data is frequently analyzed for if…then patterns, and the most important relationships are identified using the confidence and support as the two criteria.

Result Interpretation is where the recommendations are generated based on the results from the data analysis step. The classification methods assign the "ratings" to the data, and these ratings then influence what products are recommended.

2 Chapter Structure

In the subsections above, key concepts related to the topic of discussions like knowledge management systems and recommender systems along with the difference between the terms data, information and knowledge have been introduced. The rest of the chapter is organized as follows: in the section "Recommender Systems in Knowledge Management," a few related works have been discussed in detail and an analysis of each has been presented. In the section "Other Works," a list other experiments/projects/publications on the same matter have been presented. Lastly, in the section "Scope of Future Work," some scenarios/projects that can be worked on in the future have also been discussed. Following that, a list of all the sources referred to in the chapter, including research papers, books, Web sites, is given.

3 Recommender Systems in Knowledge Management

The development of knowledge management systems suffers from the fact that both the organizational and personal environments are continually changing. Recommender systems can be of help in this context as they can help to better cope with the complexity and size of knowledge structures [32–34]. They can be of use in the following contexts:

- *Understanding of Knowledge Base*: A proper understanding of the structure and basic elements of a knowledge base is imperative for its efficient development and maintenance [35].
- *Testing and Debugging of Knowledge Base*: Recommender systems can be used to recommend the minimal sets of changes required to restore consistency of knowledge bases thereby improving the efficiency of the testing and debugging process [33, 35].
- *Refactoring of Knowledge Base:* Recommender systems can be used to recommend relevant refactoring (structural changes while semantics are preserved) of the knowledge base from time to time to ensure the understandability and maintainability of the knowledge base are maintained.
- *Recommender Systems in Databases*: Recommender systems can also be used in the process of information search by improving the accessibility of databases by recommending queries [32].

Above given are the different contexts in which recommender systems can be used to enable better, easier use, and maintenance of knowledge management systems. We now take a look at the different scenarios where recommender systems have been incorporated in projects to aid with knowledge management.

Various fields have seen the implementation of recommender systems for knowledge management. We discuss examples from the engineering and academic environment, tourism, and hospitality, expertise systems in the industrial and the scientific settings as well. Following are some knowledge management systems that have been implemented using recommender systems. Presented is a chronologically ordered list of some of the work done so far.

3.1 By Natalie Glance et al.

The authors, in 1998, proposed an information technology system called the "Knowledge Pump" [36] for the purpose of supporting and connecting online communities and repositories. Its aim is to create an environment that is conducive to the creation, flow, and use of knowledge and to ensure that the right information reaches the correct people and on time. Another objective is to map repository content and community networks.

Knowledge Pump has three different design perspectives:

- Designing for the user: the user can make general recommendations or review and review any repository item. The reviews and recommendations are then collected and distributed to those who are judged to find these useful.
- Designing for the community: it provides a standard channel to the users for communication and resource sharing and also supports communities.

– Designing for the organization: using Knowledge Pump, the various overlapping communities in an organization are mapped to bring together the various disjoint parts of an organization.

Knowledge Pump implements the client–server architecture shown in Fig. 4. The client is Java-based and runs on Web browsers. The client talks to the Java-based server that performs a number of important functions such as running the collaborative filtering algorithm periodically, providing an interface to system administration and building "What's recommended?" pages for each user. These pages are saved for later and delivered to the user via the HTTP server. All the data is stored in a database which is accessed by yet another server. Any communication with the database takes place through the database server.

The Knowledge Pump uses recommender systems for item classification. It makes use of "community-centered collaborative filtering" to estimate what level of interest a user would show for the unread items in their multiple domains of interest. Here, a partial view of the social network constructed from user-input lists of trusted users bootstraps the collaborative filter. In such a bootstrapping, by giving a higher weightage to the opinions of a user's closest contacts, the system performs good from the beginning.

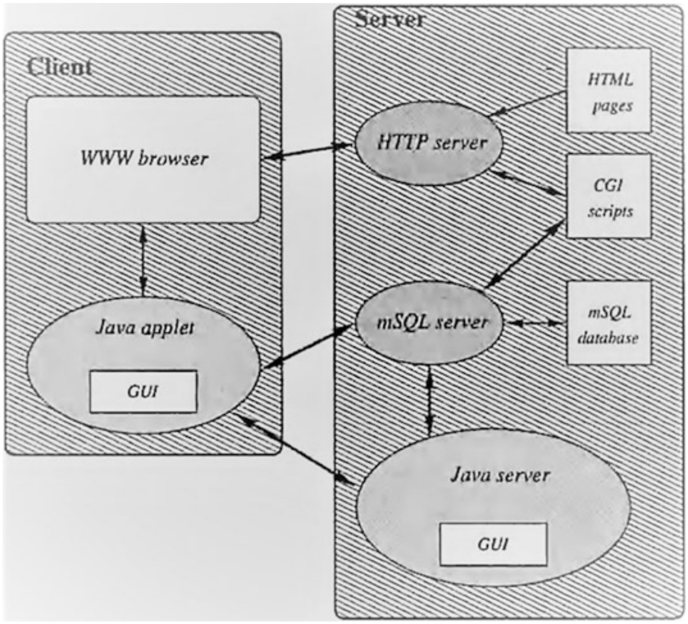


Fig. 4 Knowledge Pump architectural overview as presented by Natalie et al. [36]

The system has the following characteristics:

– Portability: means a platform-independent code. This meant using Java and suggested the application should be built to ride on top of the Web, have no browser interactions like plug-ins or cookies.
– Ease-of-use: Very low cost of installation is also achieved through Java.
– Immediate value: This implies providing a set of functionalities that are valuable above and beyond recommendations, which was achieved by building basic document management tools like search and retrieval over bookmarked items.

3.2 By Dawit Yimam et al.

The authors, in 2000, proposed the Dynamic Expertise Modeling from Organizational Information Resources (DEMOIR) framework for developing and testing expertise modeling algorithms [37–39].

Expert finders or expertise recommenders are specialized knowledge management systems that help in finding out and continually recording the "expertise" of the "experts" in an organization. They then make this expertise available to other users using recommender systems, enabling them to solve problems that exceed their personal capabilities.

The proposed framework builds upon two types of expertise models: one is the aggregated expertise (AE) model while the other is the personal agent (PA)-based model. These two approaches both have trade-offs and thus are tough to evaluate/ compare. While distributed "PA" models offer easy privacy maintenance, they suffer from the limitation of only relying on personal sources of information. Here, due to the expertise data being distributed, limited accessibility and sub-optimal utilization are issues. Scalability is also an issue as having an individual expertise modeling agent for every person overloads the network. "AE" models overcome the above-mentioned shortcomings of the personal agent-based models by allowing for an open, multi-purpose exploitation of the expertise information. Manipulation of said information and monitoring of a wide range of sources for latest data are also provided. Lastly, aggregated models also facilitate the use of both statistical expertise and knowledge-based modeling. The drawbacks though are the lack of localization, privacy of expertise data as well as a compromise on the privacy of individual experts.

The proposed DEMOIR architecture (refer Fig. 5) integrates both the aggregated and personal agent-based expertise models. It is a centralized expertise model-based modular architecture that also incorporates distributed clients as well as decentralized expertise indicator source gathering and extraction. It does so by separating functions like extraction of expertise indicators, source gathering, and expertise modeling and assigns them to specialized components for separate implementation.

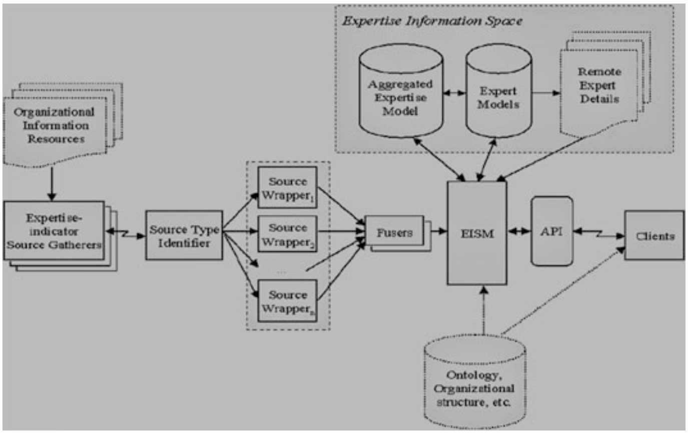


Fig. 5 DEMOIR architecture, as proposed by Yimam et al. [37, 38]

Its components can be grouped into three general functions:

- **Expertise indicator source gathering**. Performed by robots and personal agents that have data source recognition logic built into them.
- **Expertise modeling**. DEMOIR has four components to meet the user's needs. These are a source type identifier, source wrappers, fusers, and the expertise information space manager (EISM).
- **Expertise model exploitation**. Achieved using API's that provide a customized usage experience.

The characteristics of the architecture are:

- All modules are configurable and extensible, thus allowing reusability and interoperability.
- It has a combination of both centralized and distributed monitoring of expertise data, thus tackling the heterogeneity gap and privacy problems.
- It captures how the sources relate to experts and where the expertise evidence came from, and factors this information into the expert modeling process.
- It provides structure for integration of domain knowledge with statistical and heuristic methods at all steps.

3.3 *By David McDonald et al.*

The authors, in 2000, presented an architecture for the Expertise Recommender system (ER) [40] and showed an implementation as well. It implements a client–server architecture. It can support both simple clients (e.g., Web-based interface) and clients tailored to support specific features of the ER server.

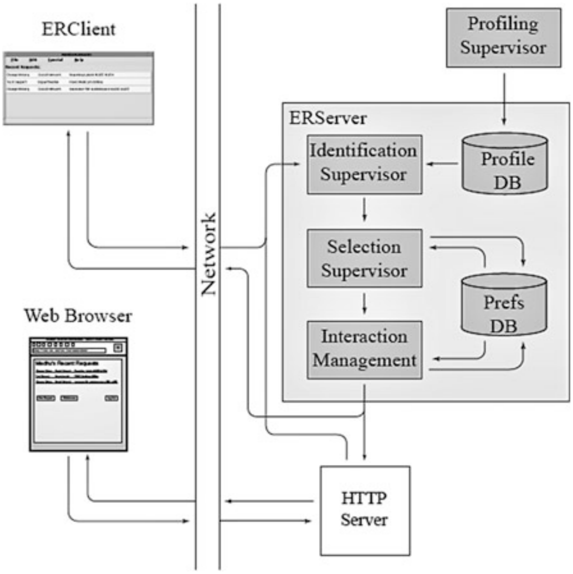


Fig. 6 Architecture of the expertise recommender system as given by McDonald et al. [40]

The ER model has a pipe and filter architecture (refer Fig. 6). It is a collection of easily extensible heuristic models, their data stores and high-level supervisors. The supervisors provide connections and general services like identification, profiling, selection, and interaction management to facilitate a specific implementation. The underlying heuristic modules are coordinated by the supervisors to provide the required services. The databases are used for providing storage for user profiles and their various preferences. All the different portions are glued together using the ER server which also handles details of servicing requests and managing connections. Client–server interactions are handled via a protocol implemented by the server.

The advantages of this system are:

- It is a flexible and open architecture that can address the various types of organizational environments.
- It has more robust organization-specific implementation by separating the technical aspects of making good recommendations from social and collaborative aspects of matching individuals.
- It uses a different approach to the ratings for creating and maintaining user profiles. Here, organizationally relevant data sources are used for profile creation and these profiles are more suited for automated expertise location.

3.4 By Joaquin Delgado et al.

The authors, in 2002, implemented the “TripMatcher” system [41] which is a recommender system for travel and hospitality. The chief motive behind this was to reduce the amount of needless expenditure on sales effort to assist customers in planning their travel. In a traditional business model, travel providers hire experts with knowledge of destinations they offer to assist customers and hope that customers can find the travel package of their choice out of the thousands of offers available.

TripMatcher plays the role of an experienced online salesperson. It interacts with customers to learn their preferences and then displays highly personalized, targeted recommendations and relevant and customized content. This allows travel providers to effectively address their customers’ needs by offering destination, itineraries, and products tailor-made for their customers’ preferences.

The recommender achieves the above mentioned by building a knowledge base using a decision tree which is built two complimentary sources. First, it uses content and ratings provided by experts and second, automatically generated ratings through text-mining of product descriptions.

The system performs the following steps/components for generating predictions:

- Content filters
- Calculating matching function
- Retrieval of result items information from the database
- Event-based calculation
- Offline attribute-based collaborative filtering.

A customized version of TripMatcher was implemented for ski-europe.com. The results of the implementation were positive with an increased conversion rate of interested people to customers. From the case study, it was evidenced that people using this system were more likely to request assistance in purchasing their travel arrangements. The increased conversion rate was seen constantly for a period of four months pointing to the consistency of the system.

3.5 By Eduardo Barbosa et al.

The authors introduced the “MISIR” recommendation module [42] into the GCC [43] in 2007 to facilitate the evaluation and dissemination of any kind of explicit scientific knowledge. The GCC was created for the purpose of aiding knowledge management in educational institutions. As numerous explicit sources of scientific knowledge, such as formulae, experiments, models, theses, publications and technical reports exist, and the number of these is also growing, to ease the process of sifting through the vast reservoir of knowledge, MISIR was incorporated into it to the GCC.

There are two stages in the MISIR approach:

1. The prediction stage: Here, the algorithm searches for documents that have not been evaluated by the user. Based on each rating given for that document by other users and on profile similarities, the algorithm calculates a grade for each non-evaluated document found.
2. The recommendation stage: Here, all the predicted grades are verified and documents with grades higher than a given threshold/reference value are selected.

As discussed earlier, the process of knowledge management has the following steps: (1) Identification, (2) Capture, (3) Selection and Validation, (4) Organization and Storage, (5) Dissemination, (6) Application, and (7) Creation.

Evaluating MISIR on this model, the following observations were made:

– It helps in the process of *identification* as the approach is directly related to the identification of explicit knowledge at an institution.
– It also helps identify individual competencies.
– As it emphasizes explicit knowledge in document form which is more useful to the user, it helps maintain essential competencies in an organization via the *capture* process.
– As MISIR tries to show only the most relevant results to the user, its approach is directly related to the process of *Selection and Validation.*
– As recommendation stage is concerned with showing/spreading relevant knowledge, it relates to the *Dissemination process.*
– In relation to the *Application* stage, the MISIR approach helps in the application of the new knowledge in various research scenarios as successful experiments, design projects, or practice, etc.
– As the proposed solution always attempts to make new, useful, and relevant knowledge available, it also helps the process of *creation* of new knowledge.

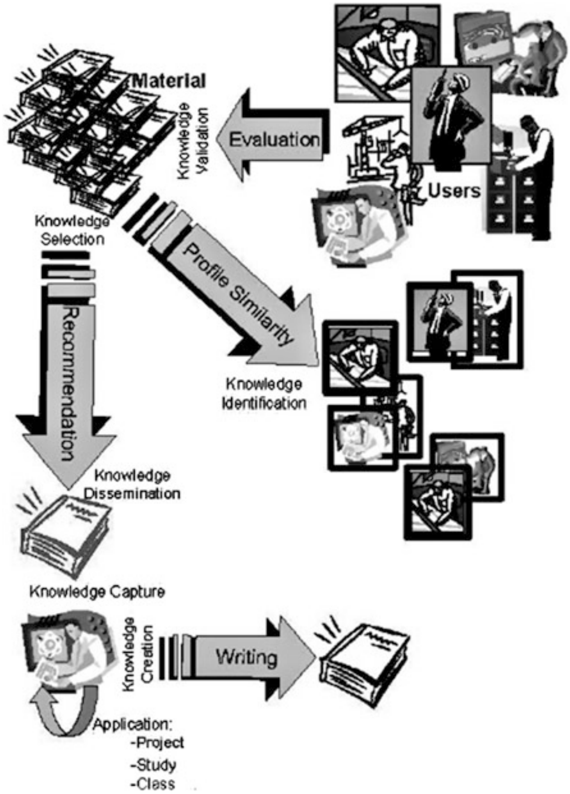
In Fig. 7 which is given below (the figure has been referred to from [42]), we get a visual representation of the knowledge transformation process performed by MISIR.

3.6 By Worasit Choochaiwattana

In 2015, the author performed a comparative analysis of item-based and tag-based recommendations to determine which approach is better suited for the task of automated knowledge dissemination [44].

The item-based recommendation mechanism, as described in Fig. 8, surveys the usage pattern of the other users of the system and makes recommendations on the basis of matches between the interests of the user and others. There are four main components that are used to implement this: *set of users, similarity measurement,*

Fig. 7 MISIR knowledge transformation process



set of interaction with knowledge items, and knowledge corpus. Cosine similarity scores are calculated between each pair of users and the users that have similarity scores greater than or equal to a given threshold, will be placed in a group together, to identify alike users, who exhibit interest in similar knowledge items.

The tag-based recommendation mechanism, as described in Fig. 9, on the other hand, recommends knowledge items by making use of knowledge tags. The main components of this mechanism are: *set of users, set of new/unvisited knowledge items, set of interaction with knowledge items, set of users' knowledge tag, and set of tags from new/unvisited knowledge items.* A cosine similarity is calculated here also to recommend knowledge items.

The experiment was conducted to compare the efficacy of the two recommendation mechanisms: one being a collaborative filtering technique (item-based), while the other is a content-based filtering technique (tag-based) in augmenting the automatic knowledge dissemination services in a knowledge management system. The performance of each system was assessed by calculating its percentage of accuracy (Eq. 1), with the mechanism with higher accuracy being more effective.

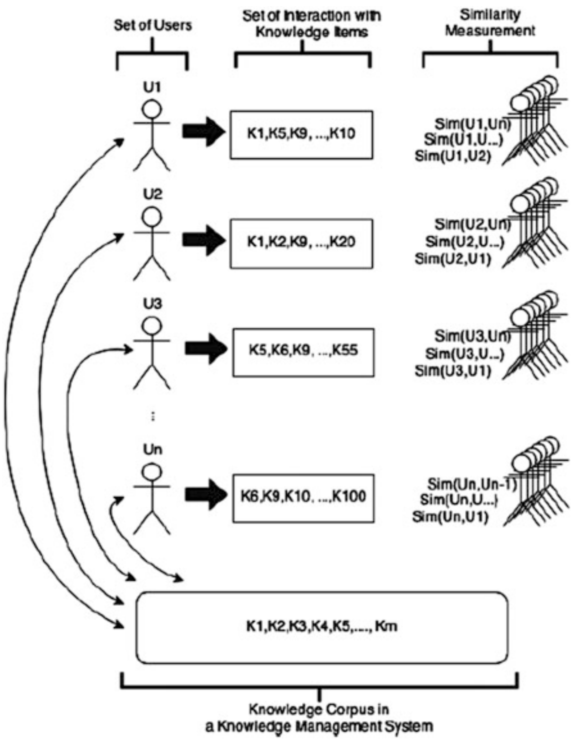


Fig. 8 Item-based recommendation mechanism by Choochaiwattana [44]

The test data was collected over a period of almost around half a year and was loaded into a KMS that had been embedded with the two proposed recommendation mechanisms. A selective group of people was chosen to use the KMS. A confusion matrix was created to measure the accuracy results for both the mechanisms.

$$\text{Accuracy} = [(\text{True\_Positives} + \text{True\_negatives})/\text{Total\_results}] \times 100 \qquad (1)$$

From the experimental results, it was observed that the tag-based recommendation mechanism (i.e., content-based filtering) provides a higher accuracy and thus performs comparatively better in the knowledge item recommendation task. The reason for this is that user's interests are better represented by a set of knowledge tags. If we only use a set of interactions to represent the user's interests, it would at best be a rough idea only. There is no guarantee the user will always have similar knowledge interests.

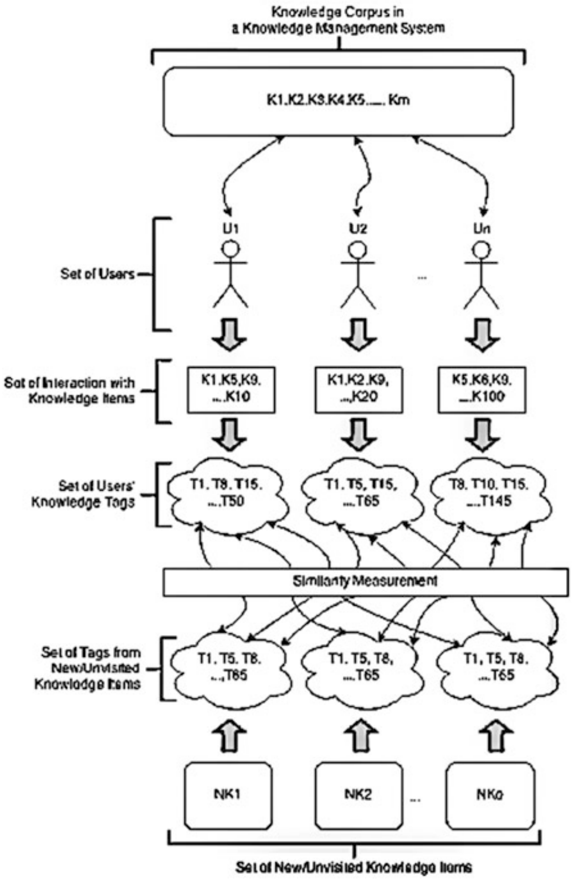


Fig. 9 Tag-based recommendation mechanism given by Choochaiwattana [44]

4 Other Works

- Linton et al. [45] describe how recommender systems can be used to enable the continuous acquisition of knowledge and individualized tutoring of application software across an organization. They propose a recommender system as a means of facilitating organization-wide learning.
- Skrzypczyk et al. [46] talk about how recommender systems can be used in the academic area to support researchers and students in their studies. It discusses the possibility of including recommender systems in the domain of personal knowledge management through different methods and techniques.
- Zhen et al. [47] tackle the problem of personal knowledge management by proposing a recommender system for the purpose of knowledge sharing in a collaborative environment.

- Verbert et al. [48] talk about how recommender systems offer a promising approach when it comes to facilitating learning and teaching tasks. In this paper, they present a framework for identifying the relevant context dimensions in "Technology Enhanced Applications" (TEL) and present an analysis of the existing TEL-based recommender systems along the identified dimensions.
- Mehrpoor et al. [49] present "Intelligent services" which is a recommender system for knowledge representation in the industry. The goal was to improve the accessibility of information and knowledge to make it easier for the stakeholders' to collaborate in the decision-making process.
- Ahlers et al. [50] examine how semantic Context-aware Recommender Systems can be applied in a design-centric engineering domain to improve interaction and navigation.
- Stenmark [51] conducted an empirical study on the use of recommender systems in organizations in order to make use of the tacit knowledge available. Using Polanyi's theories, the author shows how Intranet documents can be used to make tacit knowledge tangible without needing to make it explicit.
- Mehrpoor et al. [52] proposed a recommender system tailor-made for an engineering setting. The aim was to make use of both collaborative and content-based filtering along with semantic technologies to improve knowledge accessibility and provide relevant and accurate recommendations.

5 Scope of Future Work

A number of issues/challenges regarding recommender systems and their application to the field of knowledge management still remain open for research and exploration. The following problems still need to be tackled [34]:

- *More focus on the user perspective.* As of now, most recommender systems are focused on increasing the business revenues of companies. Approaches that pay more attention to the customer and user support are needed.
- *Sharing of recommended knowledge.* A dearth of the required recommendation knowledge is one of the major reasons why recommender systems, as of now, are not customer oriented. More customer-oriented recommender systems will act as personal assistants and require the presence of global object information for this to succeed.
- *Presence of context-aware recommenders.* New technologies should make full use of the infrastructure of mobile services to become more aware contextually. Data such as the geographical location, movement, calendar, and social network information can be exploited to provide intelligent recommendations.
- *Unobtrusive preference identification.* User preference knowledge is the most important information for generating relevant predictions. Eliciting user preferences in an unobtrusive way is a major paradigm that is faced when developing new systems.

Recommender systems need to break away from the "Filter Bubble" to able to aid their users in identifying, developing, understanding, and exploring their unique preferences. Recommender systems need to focus on how to integrate self-actualization while recommending so as to become more supportive of the consumer/human decision-making process rather than simply replacing it. A balance needs to be achieved such that recommendations are neither too personalized that they become intrusive and at the same time are not very generic that they do not account for the user's distinct taste [53].

Also, other topics for further investigation include:

- How within organizations, we can identify and exploit expertise indicator sources [39]?
- How to structure and represent expertise and expert models [39]?
- How to apply inference algorithms and rules on expert and expertise relationships [39]?
- How to support users to search, analyze, and exploit the expertise information available [39]?
- What are the integration and contextual issues for the proper deployment and positioning of expert systems in organizations [39]?
- How much a recommendation can be trusted and to ensure that recommendations are absolutely relevant and accurate as usage of information in the wrong context can have big repercussions to research [42]?
- How to improve techniques for user knowledge interest representation [44]?
- Development of context sensors to automate the acquisition of context dimensions for learning [22].
- How to tackle privacy protection challenges when capturing and using contextual data for recommendation [22]?

6 Conclusion

In this chapter, the use of recommender systems in the domain of knowledge management has been discussed. Some related works that use recommender systems to facilitate knowledge management in different industries/fields like tourism, academia, scientific research, engineering have been discussed in detail. Despite the fact that attempts at using RS's for KM have been going on for the better part of two decades now, a lot of work/research still needs to be done, as indicated by the above passage. As Etienne Wenger has very wisely quoted, "Knowledge Management will never work until corporations realize it's not about how you capture knowledge but how you create and leverage it." and the use of recommender systems to this effect seems to be apt.

References

1. Laudon, K. C., & Laudon, J. P. (2004). *Management information systems: Managing the digital firm* (p. 8). New Jersey.
2. Losee, R. M. (1997). A discipline independent definition of information. *Journal of the American Society for Information Science (1986–1998)*, *48*(3), 254.
3. http://www.stevedenning.com/Knowledge-Management/what-is-knowledge.aspx.
4. Leidner, D., & Alavi, M. (2001). Review: Knowledge management and knowledge management systems: Conceptual foundations and research. *INSEAD. MIS Quarterly, 25* (1), 107–136.
5. Quintas, P., Lefere, P., & Jones, G. (1997). Knowledge management: A strategic agenda. *Long Range Planning*, *30*(3), 322385–322391.
6. Liebowitz, J. (1999). *Building organizational intelligence: A knowledge management primer* (vol. 1). Boca Raton: CRC press.
7. Davenport, T. H., De Long, D. W., & Beers, M. C. (1998). Successful knowledge management projects. *Sloan Management Review, 39*(2), 43.
8. Gold, A. H., & Arvind Malhotra, A. H. S. (2001). Knowledge management: An organizational capabilities perspective. *Journal of Management Information Systems, 18*(1), 185–214.
9. Van Heijst, G., Van Der Spek, R., & Kruizinga, E. (1997). Corporate memories as a tool for knowledge management. *Expert Systems With Applications, 13*(1), 41–54.
10. Apostolou, D., & Mentzas, G. (1999). Managing corporate knowledge: A comparative analysis of experiences in consulting firms. Part 1. *Knowledge and Process Management, 6*(3), 129.
11. Rubenstein-Montano, B., Liebowitz, J., Buchwalter, J., McCaw, D., Newman, B., Rebeck, K., et al. (2001). A systems thinking framework for knowledge management. *Decision Support Systems, 31*(1), 5–16.
12. Ahlers, D., & MehrAndersen, A. (1997). Business consulting: Knowledge strategies. *DB/OL,* http://www.arthurandersen.com/aabc.
13. Dataware Technologies. (1998). Seven steps to implementing knowledge management in your organization. *Corporate Executive Briefing*. http://www.dataware.com.
14. Ernst & Young. (1999). http://www.ey.com/consulting/kbb/k2work.asp.
15. Holsapple, C. W., & Joshi, K. D. (2002). Knowledge management: A threefold framework. *The Information Society, 18*(1), 47–64.
16. Marquardt, M. J. (1996). *Building the learning organization: A systems approach to quantum improvement and global success*. NY: McGraw-Hill Companies.
17. O'Dell, C. (1996, December). A current review of knowledge management best practice. In *Conference on knowledge management and the transfer of best practices, Business Intelligence, London*.
18. Ruggles, R. (2009). *Knowledge management tools*. Routledge.
19. Saint-Onge, H. (1998). Knowledge management. In: *Proceedings of the 1998 New York Business Information Technology Conference,* November, TFPL, New York.
20. Steier, D. M., Huffman, S. B., & Kalish, D. I. (1997). *AAAI spring symposium on AI in knowledge management*. New York, NY: PriceWaterhouse-Coopers.
21. Van der Spek, R., & Spijkervet, A. (1997). Knowledge management: Dealing intelligently with knowledge. *Knowledge Management and Its Integrative Elements*, 31–59.
22. Wielinga, B., Sandberg, J., & Schreiber, G. (1997). Methods and techniques for knowledge management: What has knowledge engineering to offer? *Expert Systems with Applications, 13*(1), 73–84.
23. Wiig, K. (1993). *Knowledge management foundations: Thinking about-how people and organizations create, represent, and use knowledge*. Arlington, Texas: Schema.
24. Young, R. (1999). Knowledge management overview: from information to knowledge. *Knowledge Associates.* Available at www.knowledgeassociates.com.

25. Wiig, K. (1998). *The role of knowledge based system in knowledge management*. Workshop on knowledge management and at US Dept. of Labor.
26. https://en.wikipedia.org/wiki/Recommender_system.
27. Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM, 40*(3), 56–58.
28. Ricci, F., Rokach, L., & Shapira, B. (2011). Introduction to recommender systems handbook. In *Recommender systems handbook* (pp. 1–35). Springer US.
29. Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS), 22*(1), 5–53.
30. Felfernig, A., Jeran, M., Ninaus, G., Reinfrank, F., Reiterer, S., & Stettinger, M. (2014). Basic approaches in recommendation systems. In *Recommendation Systems in Software Engineering* (pp. 15–37). Springer Berlin Heidelberg.
31. Han, J., Pei, J., & Kamber, M. (2011). *Data mining: Concepts and techniques*. Amsterdam: Elsevier.
32. Chesbrough, H. W. (2006). *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press.
33. Felfernig, A., Friedrich, G., Schubert, M., Mandl, M., Mairitsch, M., & Teppan, E. (2009, July). Plausible repairs for inconsistent requirements. In *IJCAI* (vol. 9, pp. 791–796).
34. Felfernig, A., Jeran, M., Ninaus, G., Reinfrank, F., & Reiterer, S. (2013). Toward the next generation of recommender systems: applications and research challenges. In *Multimedia services in intelligent environments* (pp. 81–98). Springer International Publishing.
35. Felfernig, A., Reinfrank, F., & Ninaus, G. (2012, December). Resolving anomalies in configuration knowledge bases. In *International Symposium on Methodologies for Intelligent Systems* (pp. 311–320). Berlin, Heidelberg: Springer.
36. Glance, N., Arregui, D., & Dardenne, M. (1998). Knowledge pump: Supporting the flow and use of knowledge. *Information Technology for Knowledge Management*, *3*.
37. Yimam, D., & Kobsa, A. (2000). Centralization vs. decentralization issues in internet-based knowledge management systems: Experiences from expert recommender systems. In *TWIST2000,* Irvine, CA.
38. Yimam, D., & Kobsa, A. (2000). Demoir: A hybrid architecture for expertise modeling and recommender systems. In *IEEE 9th International Workshops on Enabling Technologies: Infrastructure for collaborative enterprises, 2000. WET ICE 2000. Proceedings* (pp. 67–74). IEEE.
39. Yimam, D., & Kobsa, A. (2003). Expert-finding systems for organizations: Problem and domain analysis and the DEMOIR approach. *Journal of Organizational Computing and Electronic Commerce, 13*(1), 1–24.
40. McDonald, D. W., & Ackerman, M. S. (2000, December). Expertise recommender: a flexible recommendation system and architecture. In *Proceedings of the 2000 ACM conference on Computer supported cooperative work* (pp. 231–240). New York: ACM.
41. Delgado, J. A., & Davidson, R. (2002). *Knowledge bases and user profiling in travel and hospitality recommender systems*.
42. Barbosa, E., Oliveira, J., Maia, L., & De Souza, J. M. (2007, April). Using recommendation systems for explicit knowledge dissemination and profiling identification for scientific and engineering contexts. In *11th International Conference on Computer Supported Cooperative Work in Design. CSCWD 2007* (pp. 715–721). IEEE.
43. Oliveira, J., Souza, J. D., Miranda, R., & Rodrigues, S. (2005). GCC: An environment for knowledge management in scientific research and higher education centres. In *Proceedings of I-KNOW'05* (pp. 633–640).
44. Choochaiwattana, W. (2015). A comparison between item-based and tag-based recommendation on a knowledge management system: A preliminary investigation. *International Journal of Information and Education Technology, 5*(10), 754.
45. Linton, F., Joy, D., Schaefer, H. P., & Charron, A. (2000). OWL: A recommender system for organization-wide learning. *Educational Technology & Society, 3*(1), 62–76.

46. Skrzypczyk, W., Bleimann, U., Wentzel, C., & Clarke, N. (2009). How recommender systems applied in personal knowledge management environments can improve learning processes.
47. Zhen, L., Song, H. T., & He, J. T. (2012). Recommender systems for personal knowledge management in collaborative environments. *Expert Systems with Applications, 39*(16), 12536–12542.
48. Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., et al. (2012). Context-aware recommender systems for learning: A survey and future challenges. *IEEE Transactions on Learning Technologies, 5*(4), 318–335.
49. Mehrpoor, M., Gjarde, A., & Sivertsen, O. I. (2014, June). Intelligent services: A semantic recommender system for knowledge representation in industry. In *2014 International ICE Conference on Engineering, Technology and Innovation (ICE)* (pp. 1–6). IEEE.
50. Ahlers, D., & Mehrpoor, M. (2014). Semantic social recommendations in knowledge-based engineering. In *HT (Doctoral Consortium/Late-breaking Results/Workshops).*
51. Stenmark, D. (2000). Leveraging tacit organizational knowledge. *Journal of Management Information Systems, 17*(3), 9–24.
52. Mehrpoor, M., Gulla, J. A., Ahlers, D., Kristensen, K., Ghodrat, S., & Sivertsen, O. I. (2015, September). Using process ontologies to contextualize recommender systems in engineering projects for knowledge access improvement. In *European Conference on Knowledge Management* (p. 524). Academic Conferences International Limited.
53. https://www.quora.com/What-is-the-future-of-recommender-systems-research.
54. https://en.wikipedia.org/wiki/DIKW_pyramid.