Artificial Intelligence in Knowledge Management: Overview and Trends

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Ilze Birzniece
Riga Technical University

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Artificial Intelligence in Knowledge Management: Overview and Trends

Ilze Birzniece, *Riga Technical University*

***Abstract* –Artificial intelligence techniques offer powerful tools for the development of knowledge management systems. Since the early 2000s, no survey describing the use of artificial intelligence capabilities in knowledge management tasks has been conducted. This paper gathers and organizes latest achievements of artificial intelligence in dealing with knowledge management issues. Accomplishment of previously set objectives in this field has been studied.**

***Keywords* – Knowledge management, artificial intelligence, personal knowledge management, distributed knowledge work**

I. Introduction

There is an agreement that businesses are no longer seen from an industrial, but from a knowledge perspective [1, 2]. It is known that knowledge is a resource. Organizations which will succeed in the global information society are those that can identify, evaluate, create and evolve their knowledge assets [2]. Information and communication technologies (ICT) support managing of knowledge. Without some degree of automation none of the contemporary knowledge management (KM) systems can succeed [3]. The life cycle of data-information-knowledge management tasks should be as short as possible if value is to be added to data, thereby satisfying the information needs of organizations and individuals [3]. Nowadays ICT are usually accompanied with artificial intelligence (AI) capabilities to get the most of what these technologies can bring.

AI methods are widely applied to pattern recognition, mathematical logics, search heuristics and many other areas. Recently KM has gained increasing attention also as one of problem domains that AI methods can be applied to [1]. Advanced AI technologies, such as neural networks, genetic algorithms and intelligent agents are providing intelligent tools e.g., for semantic text analysis, text mining, user profiling, pattern matching. Among other areas, the need for these features is present in KM tasks. Gathered in comprehensive knowledge management system (KMS) solutions, AI based technologies enable organization-wide support for the handling of knowledge. From AI perspective, knowledge representation studies the formalization of knowledge and its processing within machines. Techniques of automated reasoning allow a computer system to draw conclusions from knowledge represented in a form that is interpretable for machines [4].

Since the previous surveys of AI usage in KM tasks seven years ago some time has passed and the situation may have changed. The aim of this paper is to update obsolete reviews of AI capabilities within KM. This paper gives an overview of the present-day use of AI in KM, highlighting the recent trends.

II. Overview of Research Papers (2001-2003)

Many definitions of data, information and knowledge exist. Not discussing this subject in more details in this paper these terms will be used with [2] definitions in mind.

Data are considered as raw facts.

Information is organized set of data.

Knowledge is interpreted and meaningful information.

Wave of enthusiasm about KM hit in the 1990s, but it was followed by some disappointment that came largely from limitations of badly implemented KM software solutions [5]. In [2], organization, distribution, and refinement of knowledge are identified as the most important issues in KM. In [6] these issues are denoted as creation, integration, and dissemination of knowledge. In [7] loss of expertise is recognized as a major potential problem in organization. [7] mainly points to retaining knowledge from experienced workers in a manner that would let new or replacement members access or use it.

The extent to which AI can support enterprises in their attempts to manage knowledge has been researched. The main AI categories analyzed in context with KM are expert systems, artificial neural networks and intelligent agents [2].

Expert systems (ES) are said to be tied to KMS because they both stress the role of knowledge. Close relation can also be seen from ES definition [8]: "An expert system is a program which has a wide base of knowledge in a restricted domain, and uses complex inferential reasoning to perform tasks which a human expert could do". On the other hand, it has been argued that the classical rule-based ES rely on assumptions of certainty and are oriented towards the choice between clearly available alternatives. This position conflicts with the domain of KM, which assumes a world based on uncertainty. As the other drawbacks of ES towards KM the following issues are named.

- ES are unable to respond to vague questions or give vague answers.
- There are difficulties in the maintenance and updating of the knowledge base and learning from experience.

Artificial neural networks (ANNs) are said to have much potential within KM because of their analogy to brain functioning. The main advantage of ANNs is their ability to operate with incomplete data. They are capable of profiling users to enable information to be targeted at specific individuals according to their preferences. KM can use this technology to advance knowledge distribution and sharing. A drawback of ANNs is the ultimate need for their inputs to be presented in numeric form, which conflicts with KM.

Intelligent agents are autonomous entities which use knowledge to achieve their goals. Within KMS, intelligent agents can be used to help in the search and retrieval of knowledge, combining and creation of new knowledge. Intelligent agents can create multiple perspectives of the same situation.

Challenges that were set for the future seven years ago are the following [2, 7]:

1. Development of an integrated framework for the use of AI technologies in various KM processes.
2. Assessment of the level of AI employed in KM applications in a qualitative way.
3. Development of methods to measure KM benefits from the use of various IT.
4. Creation of hybrid systems that improve their performance over time and offer access to embedded knowledge.
5. Producing tools to elicit deeply held valuable tacit knowledge.

The rest of the paper will discuss development of AI applications in KM context, also addressing previously listed challenges and shortcomings.

III. Latest KM frameworks

Before going into details with KM advances, latest KM frameworks will be outlined to show the growing importance of AI in KM.

The revised KM framework of [9] identifies three KM subdomains. Subdomain that is focused on people-to-people interactions is Interaction-based Knowledge Management. Subdomain that is focused on automating the application of knowledge is AI. Subdomain that is focused on content-in-context activities is Content-in-Context Knowledge Management.

In [10], domain of learning within KM is divided in three types of learning, namely, human learning, organizational learning and machine or techno learning.

Human learning comprises three kinds of learning theories, know-how, know-what, and know-where, respectively. Organizational learning is an area of knowledge within organizational theory that studies models and theories about the way an organization learns and adapts. Machine learning and artificial intelligence help to automatically learn to recognize complex patterns and make intelligent decisions based on data.

The differentiation between the learning types is created so that:

- Machine learning is situated mostly within KM Tools domain.
- Human learning is situated mostly within KM Process framework domain.
- Organizational learning is situated mostly within KM Standards domain.

Both of taxonomies include AI as important issue of KM.

IV. Meeting the challenges

What has changed since challenges emerged in early 2000s? Have the expectations concerning AI and KM alliance fulfilled? As the publications in KM field imply, they have, at least to some extent. There are systems which integrate multiple AI technologies. Attempts to measure knowledge value have brought some results. Systems which improve their results also are not rare. Current efforts to represent tacit knowledge are discussed in Section VI A in context of recent KM trends. Figure 1 gives examples of AI-related technologies which are used for solving previously listed KM shortcomings. Next sections describe achievements in more detail.

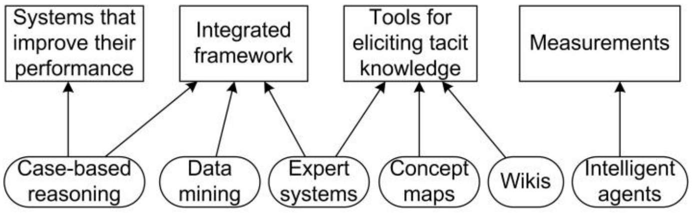

Fig. 1. Challenges for AI in KM have been addressed by several AI-based or AI-supported technologies

A. Integrated framework for the use of AI technologies in KM tasks

Complex frameworks which include more than one AI technology have emerged.. E.g., environmental decision support system described in [11] uses expert systems, data mining, and case-based reasoning in managing knowledge for environmental applications.

Decisional DNA knowledge representation allows building the experiential fingerprints of an organization by implementing a model for transforming information into knowledge [12]. In [13] Decisional DNA is defined as „a unique and single structure for capturing, storing, improving and reusing decisional experience". Sanin [12] proposes the Smart Knowledge Management System (SKMS) that is a self-learning and intelligent knowledge management hybrid platform developed to help decision makers in their daily operations. Technologies such as expert systems, simulation, statistical tools, knowledge-based systems, and multiple AI technologies are integrated into the SKMS allowing the combination of different perspectives for acquiring the required explicit decisional experiential knowledge by the means of Decisional DNA.

B. Measurements

Organization managers lack guidance in where to direct improvement efforts in their KM work. In order to justify the time and money spent on KMS and to assess its success, an organization needs to have measurement oriented culture [7]. One of possible measurements is "knowledge loss risk assessment". As long as organizations risk loosing their knowledge, e.g. by loosing their employees, any effort in capturing their expertise is bound to have some long-term value [5].

Schiffel [14] proposes a measurement model, namely, Knowledge Improvement Measurement Space (KIMS). It employs marginal utility theory in a metric space, with formal reasoning through software agents realized in Sowa's conceptual graphs, operating over a knowledge management conceptual structure. The procedure may be repeated until achieving knowledge management goals. The solution takes into account the body of knowledge related to human understanding and learning, and formal methods of knowledge organization.

Xu and Bernard [15] introduce a procedure to measure and compare knowledge value based on the knowledge value chain. It provides a template for a knowledge reference system and makes the application of knowledge measurement more effective. However, it may not solve all the problems involved in the field of KM.

Trend towards more formal measurement of KM performance is also an indicator of discipline maturity [5]. Measuring KM benefits is less implicated by AI than other addressed issues.

C. *Systems that improve their results*

To improve its results a system needs an ability to learn. One of such techniques used in KM is Case-Based Reasoning (CBR). CBR is a technique of AI that uses experience of similar past problems in solving new problems. Cases are stored together with their respective solutions, so when a new problem comes up, this information is used to solve it [16]. CBR systems use pattern matching algorithms to retrieve cases and the user can interact with the system by refining the search. CBR have been successfully used in helpdesk and call-center applications [17]. They help contributors to externalize what has been learned from experience of cases. On the other hand, frequent users of the CBR system can internalize the knowledge that is represented in the system.

The methodology of CBR directly addresses several problems found in rule-based technology [11]. Since the unit of knowledge in CBR is the case, not the rule, it easier acquires knowledge. CBR system can remember its own performance, and can modify its behavior to avoid repeating prior mistakes. Maintaining CBR system is easier than rule-based system since adding new knowledge can be as simple as adding a new case.

V. Recent trends in knowledge management (2008-2010)

Viewing KM as four knowledge conversion processes from Nonaka and Takeuchi’s framework [18], namely, socialization, externalization, combination, and internalization, AI based KM systems mainly support externalization, combination, and internalization [17].

The period between 2004 and 2007 was not very intensive in research regarding AI usage in KM. The work has livened up in recent years. Advances in KM in the last three years show new directions and thus also create space for intelligent technologies to support them. Intelligent technologies involve the use of AI. KM fields that have lately grown their importance are personal knowledge management and distributed knowledge work (see Figure 2). Different notation for fields, tasks and technologies is used.

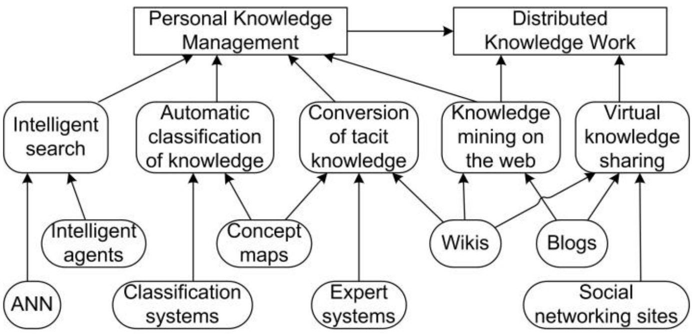

Fig. 2. Topical KM fields (*Personal knowledge management* and *Distributed knowledge work*) can be described with specific tasks they involve. These tasks, however, are supported by AI-related technologies.

A. *Personal knowledge management*

Although personal knowledge management is not a new topic itself, it has become more important in last years. Nowadays, the ability of human beings to access information is increasing, but the ability to handle information remains the same [19]. Personal knowledge management uses the computer, communications and network technology to help individuals to manage information effectively. Managing personal knowledge involves application of appropriate skills and tools [20]. Diao, Zui, and Liu [19] claim that it is necessary to apply AI to personal KM in order to obtain reliable information quickly and accurately. Their paper concerns the following main personal KM problems: information overload, unstructured information, and tacit knowledge. In order to solve these problems, such AI applications are introduced as intelligent search, automatic classification of knowledge and conversion of tacit knowledge, respectively. Also other authors confirm the relevance of these issues.

- **Intelligent search** is used to reduce the number of results retrieved by a search program and to improve result relevance. To enhance the ability of traditional search engines, the use of ANNs is proposed. After training a network with examples it is able to search for information based not only on key-words but also on content, meaning and context of the text [19]. Many activities in personal KM require an intelligent support which may be implemented in the form of intelligent agents [21].
- **Automatic classification of knowledge** is an effective way to manage the unstructured data. The classification of knowledge can be divided according to theme, subthemes, thus creating a hierarchical structure. Statistical software is used to search for the major statistical similarities between the documents. Induced rules help to make a classification of new documents [19]. Reference [22] describes China's first professional personal KM software that assists

individuals in improving learning and work in document management. It is based on the document classification and search techniques.

- **Conversion of tacit knowledge** is an important topic not only in personal KM, therefore this issue will be discussed in more details in Section 6.1.

B. Distributed knowledge work

Organizations are extending their traditional co-located work to the virtual one [23]. Situation with dispersed workers increase demands on communication and collaboration systems, ascribing the central role to interaction with ICT. In such organizations knowledge is to be transferred across four boundaries: culture, time, space, and organizations. In “virtual work” there is much in common with knowledge mining and searching on the web (that will be extended upon in Section 6.2). So-called second generation means of collaboration facilitate virtual knowledge sharing, which is very important in distributed organizations. Examples of these tools are blogs, wikis, and social networking sites. Also issues related personal KM are relevant to organizations with distributed work; as the worker in any organization should primarily organize one’s own knowledge. By enabling new ways of distributing work, technological advances have enabled new organization forms, including distributed knowledge work [23].

KM tasks stressed in the next section include the ones enabling personal knowledge management and distributed knowledge work.

VI. TOPICAL KM TASKS

Information technologies coupled with AI technologies are now called to be the major KM enablers, such as ontologies, intelligent agents, databases, data mining, browsers, decision support, XML, knowledge-based systems, intranet, groupware, document retrieval, and distributed data model [24]. Besides “traditional” KM tasks in recent years, new ones emerge. This section is devoted to the usage of AI techniques in KM issues that have been topical in the last 3 years.

A. Efforts to represent tacit knowledge

Many authors nowadays agree that representation of tacit knowledge does not seem to be unavoidable problem in knowledge elicitation practice [5, 25]. As [25] points out, inability to explicate knowledge does not imply that the knowledge cannot be formally represented. Furthermore, inability to formalize tacit knowledge as it exists in human minds does not exclude the possibility that computational systems might perform the same tasks using alternative representations.

Expert Systems. ES have not lost their importance in KM as organizational knowledge repositories [5]. They are often mentioned as important tools for explicating tacit knowledge [19, 25]. Examples provided by experts within ES are formalized and represented as rules. And, as expert knowledge is represented, it is no longer tacit. In [19] an option is proposed to collect cases from experts and apply ANNs to automatically analyze historic data when the field of knowledge is very large or not easy to determine.

Wikis. In general, wikis are designed to facilitate quick and easy content generation, collaboration, and distribution [26]. A Wiki is a set of interlinking dynamic web pages that is designed so that anyone can easily contribute and modify the content [27]. With wikis, individual users within enterprises or people all around the world can connect virtually in time or space to create, update, and share knowledge with others [26]. Wikis offer potential to capture knowledge from large groups of people, making tacit, hidden content explicit and widely available. The most popular general wiki application is Wikipedia, the multilingual online encyclopedia that relies on volunteers from around the world to contribute and edit content on any given topic. Launched in January 2001 by Jimmy Wales, it currently contains more than 17 million articles in 262 languages.

Wikis have the potential to gather knowledge from far-reaching sources. Wikis satisfy four key knowledge management needs by capturing knowledge from those who have it, converting knowledge into an explicitly available format, connecting those who want knowledge with those who have it, and linking knowledge to knowledge. In classic KM, acquisition experts are responsible for capturing knowledge from domain experts. Wikis remove the intermediary and let people share knowledge directly. Wikis are particularly effective in situations in which a large group of people want to leverage their collective knowledge to achieve some goal.

Emergent and AI related branch of wikis is semantic wiki systems which might play an important role in combining the strengths of semantic web and wiki technologies. Semantic wikis, combining the easy-to-participate nature of wikis with semantic annotations, have a strong potential to become the ultimate collaborative knowledge management system [28].

Within an enterprise, the choice of whether to implement a wiki depends on the nature of the information as well as the number of users. If a group wishes to keep information private, then wikis, unless tightly limited, are not appropriate as a means of fostering collaboration [26].

Concept maps. Concept mapping is useful for KM as a tool for externalizing expert knowledge, and to allow that knowledge to be examined, refined, and reused [16]. Concept maps provide a framework for capturing experts' internal knowledge and making it explicit in a visual form that can be easily examined and shared. The mostly used concept maps are the hierarchical ones. Concept mapping is supported by software, what makes it a useful tool for knowledge eliciting from people [5]. Concept maps can bring together knowledge elicitation and knowledge representation tasks, thus creating fertile ground for use of ES and other AI techniques which operate with structured knowledge.

B. Knowledge mining on the web

Knowledge mining on the web is a topic closely related to many contemporary KM activities, including personal KM and KM in distributed organizations. The blogs and wikis are emerging as important elements of some organizational KM systems.

Creation of specialized glossaries. In [29] the problem of domain-relevant glossaries is stressed. The first step in establishing a Web community's knowledge domain is to collect a glossary of domain-relevant terms that constitute the linguistic base of domain concepts. New communities typically have trouble in providing glossaries. Even when they're accessible, they often provide emerging knowledge in an unsystematic, incomplete manner. Authors of [29] discuss the ways of dealing with this problem. Their methodology is based on machine learning and Web-mining techniques and it is implemented in two tools. The tools use text-processing techniques to analyze both the documents' content and structure.

Blogging. Knowledge discovery in Web blogs is different from knowledge discovery in other areas. The blogosphere is the collection of all blogs and their interconnections, which can serve as a social network. Blog content often contains both structured and unstructured information. Blogs act as rich sources of knowledge therefore developing techniques for searching and mining them has become important [30].

C. Text categorization

Text categorization systems are not new but still important. Text categorization is huge and independent research area that involves AI techniques. Only few of text categorization aspects are mentioned here.

Text categorization or classification can also refer to knowledge mining in the web. KM holds the interest in organizing documents or other sources of knowledge in hierarchies of categories. Hierarchical document classification refers to assigning one or more suitable categories from a hierarchical category space to a document. Well-known examples of hierarchical categorization are taxonomies and web directories.

One of the ways to represent hierarchical categories is the use of concept maps [5]. In [31] hierarchical document classification method based on a backtracking algorithm is proposed. This method utilizes the relationships between categories in category tree finding a threshold for every category to determine whether a document could be classified into the category. The use of backtracking algorithm effectively solves the problem that a misclassification at higher level directly leads to the misclassification at a lower level.

It often happens that documents or texts belong to more than one category. In this case one of multi-label categorization approaches should be used. Multi-label categorization is also supported by software, e.g. *Mulan* library for *Weka* tool [32].

The approach proposed by [33] consists of multiple levels of classification for different hierarchies. Regularized Least Square binary classifiers are applied at the middle levels of the hierarchy to classify documents into smaller set of categories and K-Nearest Neighbor multi-class classifiers are used at the bottom to classify documents into final classes.

D. Knowledge sharing

Research in Wireless Sensor Networks (WSN) touches on many research topics, including KM [24]. One of the problems when building a knowledge-based system is knowledge sharing. There is a large diversity and heterogeneity of knowledge representation what makes it difficult to share knowledge across systems. The aim of modern Wireless Sensor networks described in [24] is to establish an AI system which is able to automatically collect environment data when necessary and make correct decisions as soon as possible. In their approach the ontologies are used to translate useful information into shared meta-knowledge, helping in decision making by using other shared knowledge.

E. Search and retrieval

In a sense, searching is locating expertise [5]. Finding the necessary information in the ocean of information is one of the hardest tasks within KM. Search and retrieval engines are primarily passive instruments. Therefore nowadays search is often accompanied with intelligent agents.

One of the tasks intelligent agents can carry out is search and information retrieval. Intelligent agents may be the way to improve search and retrieval engines, making them active personal assistants. Intelligent agents can carry out effective inquiries [19]. Search agents are most well-known and widely used ones that can be geared towards different type of searches [21]. Although agents used so far are rather simple, improvement of existing search and retrieval engines with the addition of intelligent agents allows a more comprehensive search.

F. Summary

Tables I and II give a brief overview of all KM needs and their recent AI-enabled or AI-based solutions gathered in this paper. Table I addresses challenges set by earlier research on AI in KM. Table II describes newest tasks. Tables are supplemented with references to particular use cases of given solution.

TABLE I

SUMMARY OF KM NEEDS STATED IN EARLY 2000S AND TOOLS RECENTLY USED FOR SOLVING THEM

KM need	Latest attempts to solve the need
Integrated framework for AI technologies	SKMS [12] Environmental decision support systems [11]
Measurement of KM benefits	Knowledge loss risk assessment [5] KIMS [14] Knowledge value chain [15]
Hybrid KMS that improve their performance	SKMS [12] CBR[11, 17]
Elicitation of tacit knowledge	Expert systems [19, 25] Concept maps [5, 16] Wikis [26]

TABLE II

SUMMARY OF KM NEEDS STATED IN EARLY 2000S AND TOOLS RECENTLY USED FOR SOLVING THEM

KM task	Supporting technologies
Knowledge acquisition in the web	Blogs [30] Wikis [26] Glossaries [29]
Hierarchical document classification	Concept maps [5] Multi-label classification, Mulan [32] Classification with backtracking [31] Different approaches for middle and bottom levels [33]
Intelligent search	ANN [19] Intelligent agents [19, 21]
Knowledge sharing	WSN [24] Blogs [30, 34] Wikis [26, 27, 34]

CONCLUSIONS

It is obvious that knowledge for organization or individual cannot be managed with a single technology. KM has many tasks and it needs a collection of technologies to perform them. These technologies are widely equipped with AI facilities to achieve results desired by their users.

This paper has gathered latest achievements of AI in dealing with KM tasks. It provides insight into intellectual tools available for managing knowledge. It is important to know available resources to choose from in order not to waste efforts on creating something that is already introduced. Review of literature reveals attempts to solve the challenges set in early 2000s. KM fields that have grown in their importance are personal knowledge management and distributed knowledge work. These fields are supported by many KM tasks. The paper presents a summary of most topical KM tasks and their AI-based or AI-enabled solutions. Trends in KM are knowledge acquisition in the web, hierarchical document classification, intelligent search and knowledge sharing using blogs and wikis. Paper can be also used as reference collection for studying particular topics in more details.

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Ilze Birzniece received the B.Sc. degree in computer control and computer science in 2007 and the M.Sc. degree in computer systems in 2009 from Riga Technical University, Riga, Latvia. Since 2009, she is a doctoral student at Riga Technical University, Riga, Latvia. She has been working at the Department of Systems Theory and Design, Riga Technical University, since 2007. From year 2009 she is a Researcher at the Institute of Applied Computer Systems, Riga Technical University, Latvia. Her research interests include inductive learning, data mining and machine learning.