Evaluation of Knowledge Management Technologies for the Support of Technology Forecasting

Marc Henselewski
University of Paderborn
Marc.Henselewski@notes.upb.de

Stefan Smolnik
European Business School
Stefan.Smolnik@ebs.edu

Gerold Riempp
European Business School
Gerold.Riempp@ebs.edu

Abstract

Today's business environment is characterized by highly transparent markets and global competition. Technology life cycles are decreasing due to the fast pace at which development of new technologies is progressing. To compete in this environment, it is necessary to identify upcoming innovations and trends as early as possible to decrease uncertainty, implement technology leadership, and create competitive advantage. In a parallel development, the amount of information available is already vast and increasing daily. With a growing number of features for innovation in technology, each contributing a new need for analysis, technology forecasting has become increasingly challenging. The goal of our paper is to investigate to what extent knowledge management technologies support and improve the technology forecasting process to face the aforementioned problems successfully. Consequently, we will develop a characterization scheme which works as a framework for the subsequent evaluation of knowledge management technologies and apply this to a real world case.

1. Introduction and overview

1.1. Challenge

Competition in today's business environment is intense. The influences of the rapid pace of globalization, and of the ongoing liberalization of national and international markets lead to the emergence of new problem settings and increased pressure on existing companies. Companies therefore face greater risks due to the higher number of players in the market. However, environmental influences created outside the market are not the only factors that have an impact on the complexity of existing companies' situation. The increasing speed at which innovations and new developments occur, also adds to the pressure felt by firms and their decision-makers due to shorter product life cycles and decreasing production costs. High technology companies that have high research and development (R&D) expenditures, have to specifically plan their research programs more carefully, because they run a higher risk of losing the competitive advantage when "going the wrong way". Consequently, decision-makers have a greater need to anticipate or forecast future developments and to apply these insights to business strategies and strategic innovation management in order to keep risk levels low and the company competitive. According to Bright, all "firms and governments dealing with technology have been and are doing technology forecasting. This is because each decision to explore, support, oppose or ignore a technological prospect incorporates the decision-maker's assumptions about that technology and its viability in the future" [7].

Over the last few years, firms have increasingly realized that knowledge plays a key role in the development of strategies for future success and stronger market positions. The most striking examples are technology and service-oriented companies, but retailers also engage in activities to use knowledge as factors of competitive advantage. A paradigm shift can be observed in business strategies: from a focus on tangible assets to one which prioritizes intangible assets [10], [25]. However, information and information sources' quantity is continuously increasing, and what first seemed to be the solution to several business problems, has itself become a unique problem for today's companies – too much information. In order to gain from information and to facilitate knowledge creation within a company, new ways of filtering and selecting information have to be applied. Furthermore, the nature of knowledge is highly dynamic. The value of knowledge is difficult to measure and can change from one moment to the other. Companies try to control this uncertainty to some extent and to obtain as much advantage as possible from their knowledge by integrating knowledge management paradigms into competitive strategies.

1.2. Objective and research approach

At this point, the question arises whether technology forecasting can be improved by integrating knowledge management – particularly by means of current

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knowledge management technologies. In the following, we understand the latter as instruments of information and communication technologies.

In order to answer the stated question, this article's objective is to develop a characterization scheme which integrates aspects of both fields: knowledge management as well as technology forecasting. Furthermore, selected knowledge management technologies will be evaluated through the application of this scheme to derive conclusions regarding the most promising solutions with which to support technology forecasting.

A literature study provides an overview of the related work, particularly in the technology forecasting and knowledge management literature. It also reveals the gap in the research dealing with the support of the technology forecasting process by means of knowledge management technologies. Desk and action research, e.g. the practical application of our conceptual approaches, lead us to logically deduced conceptualizations. We use case research to validate our conceptualizations inductively. The case research used in this approach is particularly suitable for problems where research and theory are in the early stages of formulation [4]. Research and descriptive processes are therefore influenced by the results from action research with corporate partners in the form of workshops and projects with partners conducted during the past few years [14], [26]. The findings are currently being applied in one company and will be expanded with further corporate partners.

1.3. Structure of the article

Section 2 introduces and defines technology forecasting and illustrates the associated standard technology forecasting process. Afterwards, this process is tailored to comply with strategic innovation management.

Section 3 leads to the development of a characterization scheme in order to evaluate the knowledge management technologies data mining, case-based reasoning, information retrieval, topic maps, and ontologies. While section 4 comprises the actual evaluation of the mentioned technologies, section 5 closes the evaluation with an integrative discussion of the findings.

The transfer of the developed insights to the real world through the discussion of an example case is covered in section 6. This is taken from an innovation-project at DETECON, Inc., conducted for Deutsche Telekom AG. The concluding section 7 summarizes the main results and suggests fields for further research.

2. Technology forecasting

As Granger points out, technology forecasting evolved from the argument that, in the long run, technological change is one of the most important influencing factors of economies [13]. Thus, technology forecasting seems to be most valuable when applied to long time horizons, which becomes even more important in strategic innovation management. For example, decisions for general strategic business planning are often based on a forecast time horizon of three to twenty years [8].

Besides longer time horizons, the scope of the results is another specific property of technology forecasting. Such forecasts "are generally concerned with the characteristics of a technology rather than how these are achieved" [13]. It was Bright who incorporated this fact into a definition of technology forecasting:

"Technology forecasting is a quantified statement of the timing, the character or the degree of change in technical parameters and attributes in the design, production and application of devices, materials and processes, arrived at through a specified system of reasoning." [7]

Other authors (for example [8]) stress that uncertainties about future developments can be modeled with the help of probabilities that help decision-makers plan for a variety of contingencies and scenarios. For this reason and the fact that technology forecasting mostly deals with long time horizons, we revised Bright's definition to attain a more rigorous and precise definition of technology forecasting:

> *Technology forecasting is a probabilistic, long-term estimate of the timing, the character or the degree of change in technical parameters and attributes in the design, production and application of devices, materials, and processes, arrived at through a system of reasoning consciously applied by the forecaster and exposed to the recipient.*

In different situations, the exact technology forecasting process can vary from a relatively simple process with just a few stages, to a process comprising a complex structure of stages and sub-processes [8]. Armstrong divides the process into six basic steps: formulate problem, obtain information, select methods, implement methods, evaluate methods, use forecasts [3]. These steps also appear in other literature, in the same or a very similar order [8], [21], sometimes in combination with additional stages.

In addition to this process structure, DeLurgio mentions that ongoing maintenance and verification are necessary to ensure that the results are valid and effective [8]. Hence, it is recommended that reality be monitored and compared to the forecasting results in order to respond to possible inaccuracies. In the context of innovation management, the suggested ongoing monitoring becomes even more important, since companies have to respond to changes as quickly as possible to stay competitive. Moreover, it can be assumed that in a large company, the individuals who conduct the

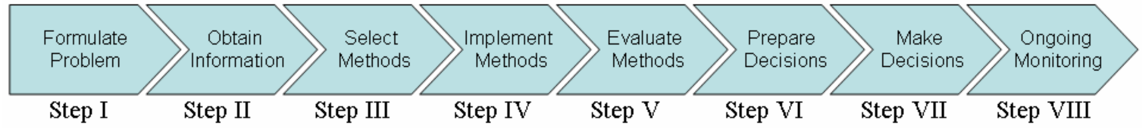

Figure 1. The technology forecasting process (following [3])

forecast and the decision-makers are not the same persons. Additional steps to prepare decisions and make decisions are therefore necessary for a complete view of the process. To include these thoughts into the process, the last stage of the process has to be split and a more detailed structure created. The resulting technology forecasting process for strategic innovation management is shown in figure 1.

3. Development of a characterization scheme for knowledge management technologies

We will develop a characterization scheme to evaluate and delineate knowledge management technologies. Since such technologies differ with respect to knowledge management as well as technology forecasting, the scheme will combine these two fields through the integration of a dimension for each of them.

When analyzing the need for knowledge management support within technology forecasting, one can argue that technology forecasting itself is a knowledge-creating process. A second look at the forecasting process reveals that each step can be regarded as a transformation process with specific inputs and outputs. Step II, for example, needs the definition of the forecasting objectives, the scope, and the time horizon as inputs. This information is utilized within the process step's activities and transformed into information of a higher complexity through the combination of the input information and new information. New relations between certain information objects are identified, leading to a greater complexity of the observed information structure. The subsequent step III also requires input from the preceding steps. It is, however, different from step II with respect to the transformation of information. While the activities of process step II increase the information structure's overall complexity, the complexity remains constant during step III, because the information is only analyzed to select suitable forecasting methods. An analysis of the other process steps shows that the technology forecasting process's steps can be characterized by their degree of varying complexity; in other words, either the level of complexity is raised or it remains unaltered. Figure 2 illustrates this relation on an abstract level without claiming to represent the actual degree of complexity increase.

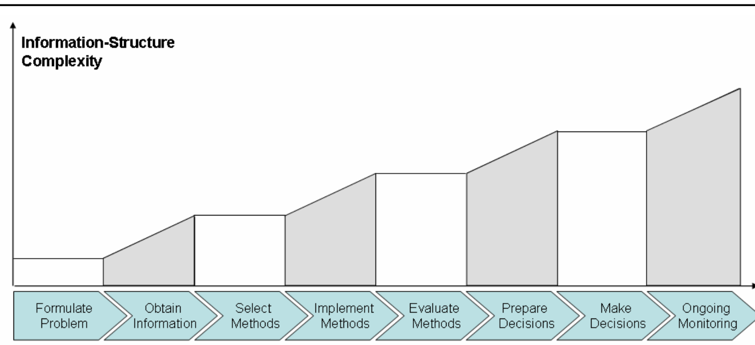

Figure 2. Information-structure complexity

On examining figure 2, it is possible to identify four steps which cause the information structure's increasing complexity within the forecasting process. These steps are obtain information, implement methods, prepare decisions, and ongoing monitoring. Reasons for these four steps' contribution to the complexity can be found when comparing each step's activities. They all have the combination of results from previous steps and newly acquired information in common, which leads to the creation of new knowledge. Such knowledge is needed to complete each process step's tasks.

Accordingly, the level of the information structure complexity is chosen as a dimension for technology forecasting, which is expressed by the four process steps identified. Such a dimension enables the categorization of knowledge management technologies according to their capability to support these four process steps, and allows an implicit description of the level of information complexity within the technology forecasting process that a knowledge management technology supports.

While the development of the technology forecasting dimension is based on the analysis of the forecasting process, a different approach has to be found to define the knowledge management dimension. As a starting point, the definitions of data, information, and knowledge should be considered. Since there is a defined difference between these terms, one can argue that data, information, and knowledge's definitions could be used as a structure with which to categorize knowledge management technologies, e.g., the category information contains all those technologies which target information. Furthermore, transformation processes are required to turn data into information and information into knowledge. A categorization structure based only on the definitions of the three terms is not capable of integrating such transformation processes, and it is obvious that there are knowledge management technologies that, for example, specifically support the transformation of data into information. Aamodt and Nygård propose a model for data, information, and knowledge which takes the three terms' specific relationships into account [1]. The model explains the processes which are needed to transform, for example, data into information, in addition to providing data, information, and knowledge's basic structure. However, with respect to the development of a dimension for knowledge management technologies' characterization from a knowledge management point of view, it can be argued that this model is not applicable. Knowledge as understood in our paper is closely linked with human action and the human mind, with learning being one way of creating knowledge. While there might be a number of knowledge management technologies which support learning, it is impossible for technologies to target knowledge itself.

Another disadvantage of such a model is the granularity. It can be assumed that there are several types of knowledge management technologies that target information, but each with a different focus or different application areas. Consequently, a finer granularity is needed which, in an optimal case, can be based on a single and continuous criterion to facilitate adoption and the development of a knowledge management dimension for the characterization scheme as stated above.

Smolnik, Kremer, and Kolbe suggest an approach, called "the continuum of context explication", which fulfils the mentioned requirements and is based on the importance of context, with context explication meaning "discovering implicit meanings and expressing those meanings explicitly" [24]. The authors stress that context is an important aspect that many definitions of knowledge have in common [24]. They moreover compare several definitions of context. Dey and Abowd, for example, define context as follows:

"Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves." [9]

Besides the definition of knowledge, context also plays an important role in the definition of information. Nonaka and Takeuchi argue that "knowledge, like information, is … context-specific and relational." [19] Smolnik, Kremer, and Kolbe found that knowledge management technologies "focus on contextual information in different ways and with varying intensity" [24]. Consequently, the authors present five approaches to "find and use information objects and contextual information …, each with a differing degree of context and explication ease" [24]. The continuum distinguishes five different approaches:

- The data approach: Data are symbols or signs without a meaning or context. Thus, context cannot be explicated. Nevertheless, technologies can be applied to transform data into information or domain-specific knowledge. The data approach encompasses these methods.
- The information approach: Most important for the definition of information is that information includes meaning and a specific context. However, the "context is … interwoven with the content and difficult to conceptualize, which means that the methods implemented to find requested information objects have to rely on the content and cannot access contextual information." [24]
- The descriptor approach: The addition of explicit contextual information to information objects and thereby providing context aware methods for information search and discovery is called a descriptor approach.
- The meta-context approach: This approach extends the descriptor approach, as explicit contextual information no longer resides only within information objects, but is integrated into a meta-layer which independently lies above and spans a variety of information.
- The knowledge approach: The knowledge approach focuses on the human being and considers characteristics of knowledge. It is about knowledge creation through actions like communication, construction, or cognition.

The continuum's consideration of context and its explication offers a continuous criterion with which it is possible to distinguish different knowledge management technologies. This fact makes the continuum of context explication an ideal basis for the development of a knowledge management dimension. Each approach forms one category which can be used to classify knowledge management technologies. The only exception is the knowledge approach. Since the knowledge approach is closely linked to the human mind and human action, knowledge management technologies cannot explicate person-specific context. This approach is therefore not used within the knowledge management dimension.

The combination of the developed technology forecasting dimension with the dimension for the knowledge management perspective, results in the creation of the context-complexity matrix. Such a matrix allows the characterization of knowledge management technologies with respect to the degree of context as well as the technology forecasting process's degree of information structure complexity. The background of each dimension implicitly provides further characteristics of the classified knowledge management technologies. A categorization of, for example, the meta-context approach within the knowledge management domain and step VIII in the technology forecasting domain means that the knowledge management technology is capable of supporting step VIII's high complexity and also comprises a high level of explicit contextual information.

4. Evaluation of knowledge management technologies

The breadth of available knowledge management technologies ranges from very simple to very complex ones. The set of knowledge management technologies for the following evaluation has therefore been selected to represent this breadth, namely: data mining, case-based reasoning, information retrieval, topic maps, and ontologies. We evaluate these technologies in the following with respect to the presented characterization scheme.

Data mining

Authors in the field of data mining often state that the identification of specific patterns enables the extraction of knowledge which is embedded within databases (e.g. [15] or [18]). This view is not fully precise. The consideration of data mining applications like market basket analysis, fraud detection, or risk analysis leads to the thought that data mining functionalities enrich data through the identification of patterns or classes in such a way that a person familiar with the domain is capable of deriving a meaning from the presented results. Hence, domain-specific information is generated which can then be combined with other information and knowledge to create new knowledge. But data mining contains no functionality which particularly supports this combination of information. Considering the continuum of context explication as the dimension for a knowledge management categorization, the discussion above can be summarized by assigning data mining to the category 'data approach'.

With respect to technology forecasting, Armstrong argues that "an immense amount of research effort has so far produced little evidence that data-mining models can improve forecasting accuracy." [3]. Thus, the quality of forecasts which are solely based on data mining is debatable and, consequently, also the support of step IV. However, it is our opinion that data mining can be successfully utilized to facilitate specific tasks within steps of the technology forecasting process other than the implementation of forecasting methods. As we explained in section 3, step II and step VIII require the analysis of great amounts of information with respect to specified criteria. In step II, information is needed which can be associated with the forecast's objectives as defined during step I, while an ongoing analysis of information based on the results of a forecast is required within step VIII. In combination with other technologies, data mining might be a suitable way to improve the efficiency of identifying interesting information objects through classification and association analysis. Data mining can therefore be assigned to the categories 'step II' and 'step VIII' of the technology forecasting dimension.

Case-based reasoning

Compared to data mining, case-based reasoning is a concept which targets information rather than data. A case provides the solution to some problem which can basically be viewed as providing domain-specific information [22]. Case-based reasoning comprises certain functionalities which allow the emulation of cognitive processes in order to generate solutions [22]. These functionalities are the capability to adapt old cases to suit the needs of new cases and the fact that a system enlarges its case base by evaluating and retaining cases which have either been solved, or provide information about faults. Systems following the structural case-based reasoning approach [6] integrate these functionalities and apply general domain knowledge to a model to improve case storage and retrieval, thereby putting the different cases into a certain context. The context is defined by a set of features which are used to index a case and to determine similarity between different cases [2]. Thus, features are descriptors of information objects and the corresponding context.

On the other hand, there are also case-based reasoning systems which do not have an underlying domain model, like those which use the textual case-based reasoning approach [6]. Such systems work directly on the information and utilize certain algorithms to compare and match new cases with those contained in the case base. Consequently, case-based reasoning belongs to the category 'information approach' to the same extent as to the category 'descriptor approach' with respect to the knowledge management dimension.

Considering the dimension for technology forecasting, an appropriate characterization and the corresponding identification of the potential for supporting the technology forecasting process is a more difficult task. Gaines and Shaw argue that in the case of technology and innovations it seems that the past is not appropriate for predicting the future [11]. Case-based reasoning, however, is designed around previous experiences. This leads to the conclusion that case-based reasoning cannot be applied to the execution of technology forecasting activities. It cannot therefore be assigned to the category 'step IV' of the technology forecasting dimension. Moreover, taking the requirements of step II and step VIII into account, it is doubtful that case-based reasoning is a useful method with which to support these activities. Both steps need to handle a great amount of new information and to put this information into context, either to achieve a clearer perspective of the forecast's scope, or to collect information with which to monitor the forecast's results.

Case-based reasoning is not a method which is intended for the identification of new information. It cannot therefore be assigned to the categories 'step II or step VIII' of the technology forecasting dimension.

Nevertheless, it is case-based reasoning's purpose to support decisions and to solve problems. Therefore it is an appropriate technology for application during step VI. More precisely, case-based reasoning can be used to support planning activities [17]. A company which has a long experience in pursuing and developing innovative technologies might profit from its knowledge when a new technology is about to be developed or integrated.

Information Retrieval

On considering the definitions of each single category of the knowledge management dimension, it seems obvious that information retrieval belongs to the category 'information approach'. In general, such a categorization appears to be reasonable since information retrieval targets raw information. Smolnik, Kremer, and Kolbe argue that although information itself comprises content and context, the context is interwoven with the content and thus difficult to explicate [24]. As a result, technologies which do not include additional explicit contextual information rely only on content or its representation for use within search functionalities. Clearly, this is true of most existing information retrieval conceptual models.

On the other hand, one can argue that some forms of information retrieval also integrate explicit contextual information into search and retrieval methods. While Smolnik, Kremer, and Kolbe state that "authors have to provide [explicit contextual] information at the time of creation" [24], the consideration of the concept of aboutness, as introduced by Ingwersen [16], allows an additional perspective. On considering the fact that some information retrieval systems are based on the creation of index terms through document analysis and alignment with a specific domain by individuals, we argue that such indexes represent the indexer's aboutness and therefore also the context of the individual who analyzes the documents and creates the index. Nevertheless, in the same way that indexer aboutness differs from author aboutness, the author and indexer's contexts vary. In general, the characterization of information retrieval by assigning it to the category 'information approach' within the knowledge management dimension is a reasonable outcome; however, the exceptions as discussed above should be taken into account. Information retrieval will therefore be categorized by mainly assigning it to the category 'information approach' as well as partially to the category 'descriptor approach'.

Within technology forecasting, certain process steps include the need to identify information when a large amount of it is available, namely, step II, step IV, and step VIII. The difference between these steps' information need is that the first two steps require a broad range of new information with respect to the selected forecasting scope, while the latter step utilizes specific information which is closely linked with the developed technology forecasts in order to compare them to reality. Therefore, an efficient way to identify and assess relations and derive consequences from specific information objects is more important than simply the retrieval of interesting information from a large amount of various, available information. It is a common assumption among researchers of information retrieval that searching within such systems is an iterative process [23]. A user starts with some sort of query and evaluates his own understanding of the information needed with the help of the first result set. Either the information is sufficient – it results in the retrieval of additional information through references or alike – or a user realizes that the request has to be completely revised. Reasons for this can be found when taking into account that users are only able to describe what they need based on what they already know. These arguments lead to the conclusion that information retrieval is not applicable to step VIII of the technology forecasting process and, instead, can be characterized as being able to support steps with a need for a wide range of new information, thus step II and step IV.

Topic Maps

Topic maps provide methods with which to navigate associatively across large amounts of available information in a conscious manner, enabling a systematic identification of information and creation of new knowledge by the user. This is possible by detaching the information source from the context used to find the information which results in topic maps being "information assets in their own right, irrespective of whether they are actually connected to any information resources or not" [20]. Moreover, topic maps support "managing the meaning of the information, rather than just the information" [12]. An explicit context, called meta-context, is used to organize available information in such a way that more efficient search methods can be applied. Hence, the meta-context is the most characterizing aspect when discussing topic maps, they thus clearly belong to the category 'meta-context approach' when considering the knowledge management dimension of the context-complexity matrix.

Because a topic map describes certain domain knowledge, it can be very useful when created to represent the forecast's scope. Such a topic map comprises the different technologies and research areas within the focus of the company which conducts the forecast. Associations can be used to link technologies in order to express influences and relations among those technologies. Any information to which the topic map is applied can then be categorized with respect to the forecast's scope, facilitating identification of valuable information. Furthermore, once a comprehensive information repository exists, the topic map can be used to relocate information and to relate it to the forecasting activities' results. Hence, topic maps also provide additional value when used within step IV and step VI. Identifying specific information which correlates with the forecasting activities' results is especially important within step VIII. Topic maps' filtering and localization capabilities help to achieve a more precise analysis of available information and, hence, a more efficient monitoring process overall. In general, topic maps have the potential to increase the efficiency of each technology forecasting step in the context-complexity matrix, because they can be tailored to a forecast's scope and thereby reduce the available information's complexity to a manageable level.

Ontologies

Ontologies are a means to provide a resource which unambiguously determines the meaning of terms and their relations to other terms within a certain domain [5]. This structure is an autonomous construct without links to specific information resources. With respect to the knowledge management dimension of the context-complexity matrix, it is quite obvious that ontologies belong to the category 'meta-context approach'. The reason for this is that explicit context structures are created which are independent of specific information resources and can be viewed as an information resource themselves. Therefore, relations have to be created between an information resource and ontologies by means of explicit contextual information and specific references that are added to the information resource. This methodology clearly does not fit into any other category on the knowledge management dimension than the meta-context approach.

The same reasons that lead to the obvious characterization of ontologies as a meta-context approach, hamper categorization with respect to technology forecasting. The question arises: which of the technology forecasting process's steps and activities benefit from the development and application of an ontology? Following the premises regarding the benefits of ontology application as presented by Zelewski [27], possible applications for ontologies within technology forecasting can be derived. Zelewski argues that the knowledge intensity of the tasks which are to be accomplished, and the degree with which the knowledge backgrounds of the parties involved in an interaction differ, both influence ontologies' importance as a means to improve the considered process tasks' efficiency. When conducted for strategic innovation management, many technology forecasting methods, such as, for example, the Delphi method [3], [8], are aimed at transferring individuals with different backgrounds' specific knowledge into statements about future technological innovations and developments. Thus, Zelewski's premises are true with regards to technology forecasting. As a result, only the category 'step IV' seems to be suitable for ontology application's characterization within technology forecasting for strategic innovation management, but it is limited by the technology forecasting methods chosen.

5. Discussions

Obviously, some of the technology forecasting process's steps can be supported by more than one knowledge management technology. Therefore, the question arises: which single technology or which combination appears to be the most promising with which to support and improve this process?

To answer this question, it is helpful to consider technology forecasting for strategic innovation management with respect to the type of input each

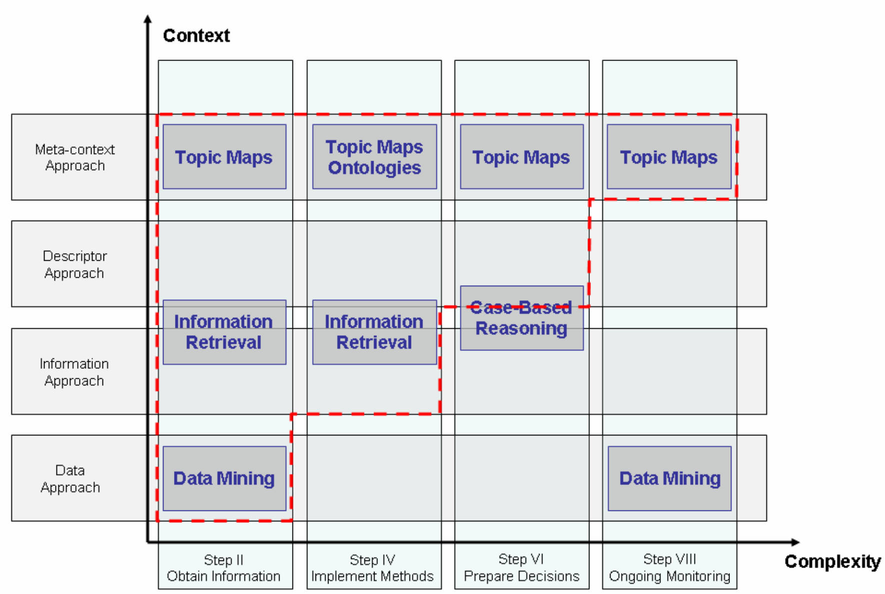

Figure 3. The context-complexity matrix

process step requires. We have shown that the complexity of the information structure within the technology forecasting process increases in the course of the process. We argue that context too becomes more and more important. At the beginning of the process, the importance of context as well as the information structure complexity is rather low, but in the end, the degree of complexity and context importance reaches a maximum. As a result, the context-complexity matrix has to be refined to integrate strategic innovation management's focus in such a way that only the upper left triangle represents possible solutions, which are promising ways of supporting technology forecasting steps through knowledge management technologies as presented in figure 3.

A striking point of the context-complexity matrix is the fact that topic maps are capable of supporting each process step in a certain way. However, topic maps require some knowledge about the domain and its topics for their generation, while information retrieval provides functionalities which require less prior knowledge and can be used to gather a first broad variety of information. This can be especially helpful during the first phases of technology forecasting research efforts. Such information can then be analyzed to generate the needed topic map, which corresponds with a technology forecast's scope. Later on, the topic map can be used to classify and organize further information and, hence, allows a more systematic way of discovering additional information.

In summary, we can state that a knowledge management system which is based on topic map technologies and integrates information retrieval functionalities as extensions to those provided by the topic map, is the most promising solution with which to support technology forecasting for strategic innovation management. In order to verify the theoretical results, we test them within a real world scenario.

6. Real world case

We have applied our findings to a project conducted for Deutsche Telekom AG at DETECON, Inc. a technology and management consulting company with a focus on innovation engineering. The main objectives of the project are the identification of technology trends and developments with the ability to open new opportunities and the assessment of their innovation potential. The technology forecasting process at DETECON, Inc. differs in two main aspects from the generic process as presented in our paper. Firstly, the scope is not necessarily defined at the beginning of the process, but a broad general perspective can be chosen. This is comparable to what Reger calls "core technologies" and "white spaces" [21]. Secondly, DETECON, Inc. does not fully control the process. At the beginning of a phase, comparable to step VI, Deutsche Telekom AG is in charge and is responsible for the remaining steps and activities.

Due to section 5's results, a system based on the central utilization of topic maps seems most promising in improving technology forecasting efficiency. One characterizing aspect of technology forecasting at DETECON, Inc. is the flexible scope which different steps and activities inside the process require. Topic maps can be tailored to suit such a flexible use. Regarding the process at DETECON, Inc., the development of one single comprehensive topic map which represents the applied domain knowledge's basic structure as, for example, technologies and their relations and influences, could offer a solution. Sophisticated methods, like a topic map concept called scope, can then be used to restrict this topic map to the necessary range for single activities. This is sufficient because all DETECON, Inc.'s forecasting activities deal with technology and innovation developments and their influences on Deutsche Telekom's technology and business situation. A topic map which has been built and maintained for the corresponding domain, and which can be tailored to represent only the available information's subparts through the exploitation of topic maps' scope attribute, provides an efficient solution for the flexibility requirement.

Obviously, the nature of a topic map also facilitates organization and reuse of information, and therefore fulfills another requirement with respect to technology forecasting at DETECON, Inc. Information which has been used once can be stored in a repository and can be accessed through the topic map. It is also associated with analyses, contacts, or other related information. Therefore, knowledge structures once generated can be represented by the topic map and the recovery of such structures is facilitated. In addition, a topic map can be used to categorize new information by determining the topics which occur in the new information. This functionality can be combined with automated information retrieval methods. The information is retrieved from some source (most likely within the WWW), it is analyzed with respect to the occurring topics, and then added to the information repository. This process facilitates the identification of valuable new information without the need to analyze all new available information manually. Because the information is available through the topic map, it can be accessed when needed.

The switch of control for and responsibility of the process from DETECON, Inc. to Deutsche Telekom AG, leads to the facilitation of knowledge transfer as another requirement of a system to support the technology forecasting at DETECON, Inc. Once a technology is considered interesting and relevant by Deutsche Telekom AG, a more detailed technology profile is created which is then sent to Deutsche Telekom AG. The integration of the mentioned profile documents into the structure of a topic map, as well as their association with the main topics and further relevant information about the corresponding technologies facilitates this task. The technology-related knowledge can be transferred with the help of the topic map by allowing access to the profile documents and their related information. Personal meetings can then be used to discuss the technology and business consequences, creating additional knowledge which goes beyond the technology itself.

The challenge of such a system, however, is the maintenance of the topic map. A fully manual maintenance implies the awareness of new developments. Therefore, methods have to be found which facilitate this task by suggesting new topics and associations. Statistical methods as applied within automatic indexing can provide a useful starting point for the solution of this problem.

In summary, topic maps provide the needed degree of flexibility, facilitate information organization and reuse as well as knowledge transfer. Therefore, a system which bases on topic maps will be considered the solution to the increasing difficulties related to technology forecasting at DETECON, Inc.

7. Conclusions and future areas of research

As shown, knowledge management technologies play an important role in supporting the technology forecasting process as part of strategic innovation management. As there are several possible knowledge management technologies, the real task for technology forecasting begins with the selection of the appropriate technologies for each process step. We have therefore evaluated several knowledge management technologies, each explained according to their main characteristics, benefits, and constraints, focusing on the support of the technology forecasting process's different steps and aligning them into the proposed context-complexity matrix. The successful application of our theoretical findings has been shown by the real world case, realized at DETECON, Inc. and Deutsche Telekom AG.

To enrich our proposed model of context-complexity, we envisage at least three areas of future research:

- Firstly, within innovation management most forecasting is done via the analysis of information as shown by the example of DETECON, Inc. and Deutsche Telekom AG. We have to prove whether the integration of other forecasting methods, for example extrapolation methods, into the supporting system could lead to a higher forecasting quality and decreased uncertainty with the aim of automating a major part of the forecasting process and achieving improved decision support.
- Secondly, we will analyze whether knowledge management technologies are also capable of supporting single technology forecasting methods.
- Thirdly, we will validate and expand our findings in further real world cases in order to verify the theoretical results and ideas of this paper and to identify further aspects with the potential of increasing technology forecasting efficiency, improving innovation strategy formulation, and thereby creating and sustaining competitive advantage.

The development of the context-complexity matrix and its application to selected knowledge management technologies has shown that within technology forecasting an increasing amount of information structure complexity leads to an increasing need for context explication. Information repositories are less useful without the application of explicit meta-contexts which facilitate the discovery of needed information. While technologies like data mining or case-based reasoning provide only a marginal efficiency increase, topic maps possess a broad applicability and have the potential to increase efficiency greatly.

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