CONCEPTION OF A KNOWLEDGE MANAGEMENT SYSTEM FOR TECHNOLOGIES

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ABSTRACT

For strategic product and technology planning of intelligent technical systems a holistic process and tool is needed to support a company in the innovation process. An important aspect within the innovation process, is technology planning. The Heinz Nixdorf Institute developed a technology-planning concept, which is supported by an Innovation-Database. The Innovation-Database synchronizes aspects from the market pull and the technology push. Furthermore, it is used as a knowledge management system for innovations and technologies. The challenge is filling the technology pool with a minimum set of technologies in order to use the whole functionality of the Innovation-Database. Many resources are needed in order to fill the technology pool or to update it. There is in increase in information in the World Wide Web and most of the information is fuzzy. Our approach is to identify them automatically by using crawler technologies. Therefore a software tool was developed, which automatically crawls for technologies in the database of the European Patent Office and in the journal database IEEE Xplore. In these data sources, the tool identifies technologies automatically in natural texts, prepares the data and visualize them. It is not suitable to scan a text for a defined set of technologies in a dictionary, because then the tool is not able to find new technologies or to detect weak signals.

In this paper, the architecture and features of the software tool is described. It uses text mining-methods to detect technologies in unstructured, fuzzy data. As input data, the user has to provide a search field, which the search is performed for. Furthermore, the data sources have to be defined. The tool crawls these data sources in order to identify technologies, which can be relevant for a given search field. The tool suggests newly identified technologies for the search field, which are generally relevant. The user has to decide whether those technologies are important for him. This information is used as feedback for the text-mining model to improve the precision of future analyses. In order to support the user, a suggested technology is automatically provided with further information, like a description and an estimation of technological maturity. With this information a user can start an evaluation of the technology. For every technology a datasheet is created with detail information. It can easily be customized for specific demands. All technologies can be visualized on a radar. The radar shows all technologies for a search field according to its relevance. These information is used for strategic product and technology planning.

Key words: text mining, big data, technology planning, knowledge management, technology intelligence.

INTRODUCTION

Developing intelligent technical systems become more and more complex. The product lifecycle becomes shorter and the demand in using state of the art technologies becomes more important (Ponn and Lindemann, 2011). Especially technology-oriented companies are interested in the newest technologies to gain an advantage against their competitors (Schuh et al., 2014). In addition to that the dynamics in developing new technologies rises. It is important for a company to know recent and new technologies in their technological domain and to consider technology intelligence in their product engineering process, especially in the strategic product planning. Only a few companies already use techniques to find information about technologies systematically in the World Wide Web (Schuh et al., 2014). Especially small and medium size companies struggle the challenge of information explosion because technology intelligence is too extensive. Considering the amount of data which was produced in 2013 (4.4 zettabyte) and is estimated in 2020 (44 zettabyte) it is obvious that it becomes even more extensive to find the right information in the data (IDC, 2014). The main challenge is that especially in our linked world in which a lot of information is available in distributed data sources, it becomes more difficult to find the right information manually, let alone weak signals.

In the early phases of product engineering, strategic information of market, business environment and technology is gained in order to evaluate chances and risks of this information. To support this process a software tool is necessary to find and structure information for evaluation. In the following a new tool for technology intelligence is described which is used in strategic product and technology planning in the product engineering process.

TECHNOLOGY INTELLIGENCE AS PART OF STRATEGIC PRODUCT PLANNING

Due to our experience, the product engineering process to build innovative products and services is not a straight process of tasks. Furthermore, it is a cyclic process of the domains “Strategic Product Planning”, “Product Development”, “Service Development”, and “Production System Development”. Figure 1 shows the cyclic innovation process with the mentioned domains (Gausemeier et al., 2014).

In detail, the first cycle represents the strategic product planning. This cycle contains Foresight, Product Discovering, Conceptual Design of the Product and the Business Planning. Tasks in there are the identification of future success potentials and business options as well as a systematic finding of new product and service ideas. Future success potentials contain besides market potentials also technological potentials.

The second cycle (Product Development) contains a holistic approach of designing new products considering the domains of mechanics, electronics, software engineering and control systems. In accordance to that cycle the third (Service Development) and fourth cycle (Production System Development) should be performed parallel to the second cycle. Service development contains the conceptual design of a service idea according to a product. In order to prove that a product can be produced the product and production system planning depend on each other. Production system planning specifies aspects like place of work, working appliances, logistics and process.

Within the first cycle, changes of markets and technologies are anticipated. These changes cannot be predicted for sure, but can be forethought. Traditional methods are among others scenario technique, trend analysis and Delphi studies (Gausemeier and Plass, 2014). Information about technologies can be found in the World Wide Web in journal databases, patent databases and even in forums. This information is fuzzy and mainly unstructured. ANSOFF shows that technological advancements can be detected by so called weak signals (Ansoff, 1976). Such signals can be recognized in the present and suggest future technological advancements. The need for action is to identify weak signals in the World Wide Web automatically and to store them in a proper way in a database in order to evaluate it. There exist two important approaches to identify new technologies and update already collected technologies, called scanning and monitoring. Scanning is defined as a long-term non-directional task to find new technologies and monitoring is defined as a directional task in a defined period of time to observe technologies or search fields for new technologies (Wellensiek et al., 2011). Search Fields are defined as categories in which new technologies are searched. Besides scanning and monitoring, an early evaluation of technologies is important to anticipate chances and risks of those technologies. The whole process of finding, evaluating and monitoring can be summarized with the term "technology intelligence".

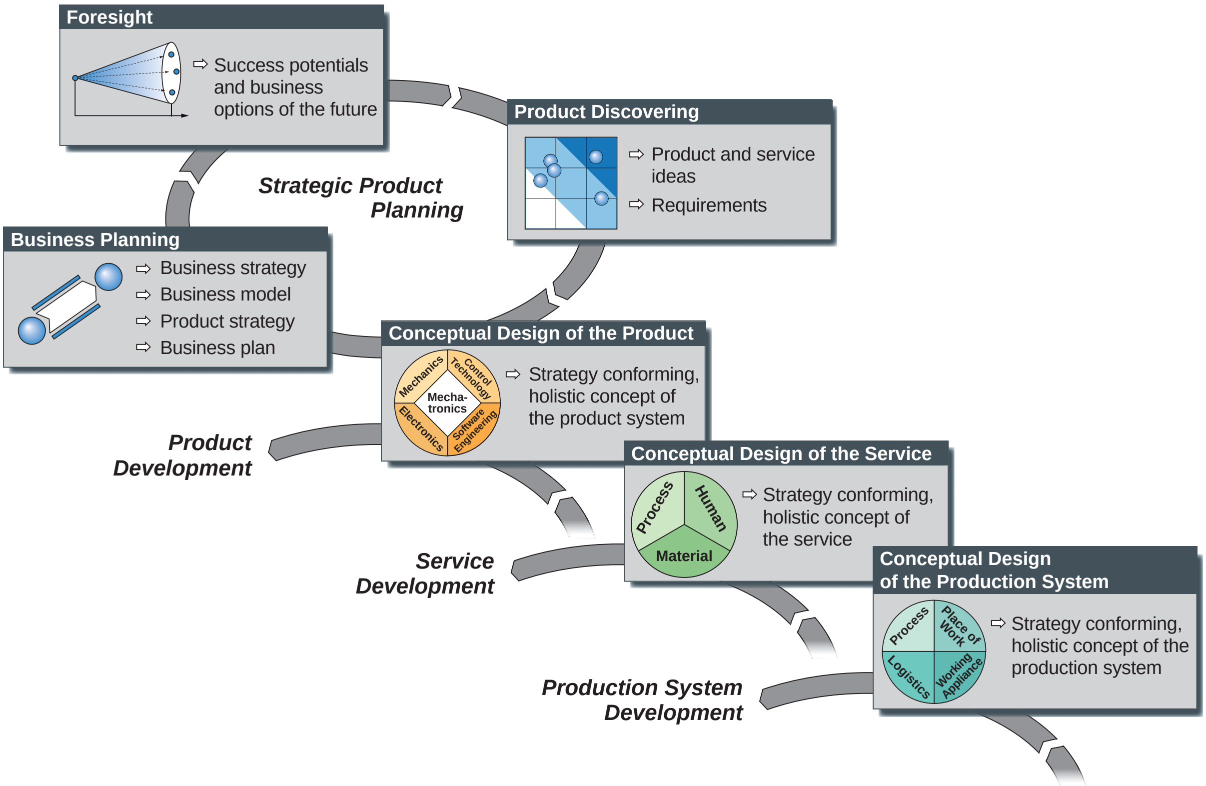

Figure 1: Generic reference model of product engineering, Source: Gausemeier et al., 2014

The technology-planning concept of the Heinz Nixdorf Institute

Software tools for technology planning are already widespread in industry. ISENMANN discovered already in 2008 that such tools are widely used (Isenmann, 2008). In the last few years, we discovered similar findings and confirm that a high amount of companies is using such tools. The primary use of it is for storage and evaluation of innovation ideas. There are many tools, which cover single aspects of the strategic product and technology planning (Gausemeier et al., 2011). Especially information about markets and business environments are strictly divided from technological information. In our approach, we connect aspects of **market pull** in form of information over future markets, which are derived from scenario analysis with aspects of **technology push**. For technology push, we offer a technology pool, which can lead to innovation ideas as well as insights from markets. Both aspects have to be synchronized and new innovation ideas have to be consolidated in an innovation roadmap (Eversheim, 2002), (Westkaemper and Balve, 2002).

The demand of a holistic software tool to support the strategic product planning is obvious. In each task a lot of information occur which has to be interpreted, transformed and saved into the innovation tool. This information contains aspects of technology push and market pull, which are important for making decisions in the whole process. Therefore, we developed the Innovation-Database [Brink et al., 2007]. This tool is illustrated in figure 2. The data model has four relevant entities: technologies, functions, product ideas and market segments. The entities scenarios and influence factors projections are not important for this paper. All entities are connected in a relational data model and are saved in a central database. This is illustrated in the centre of figure 2.

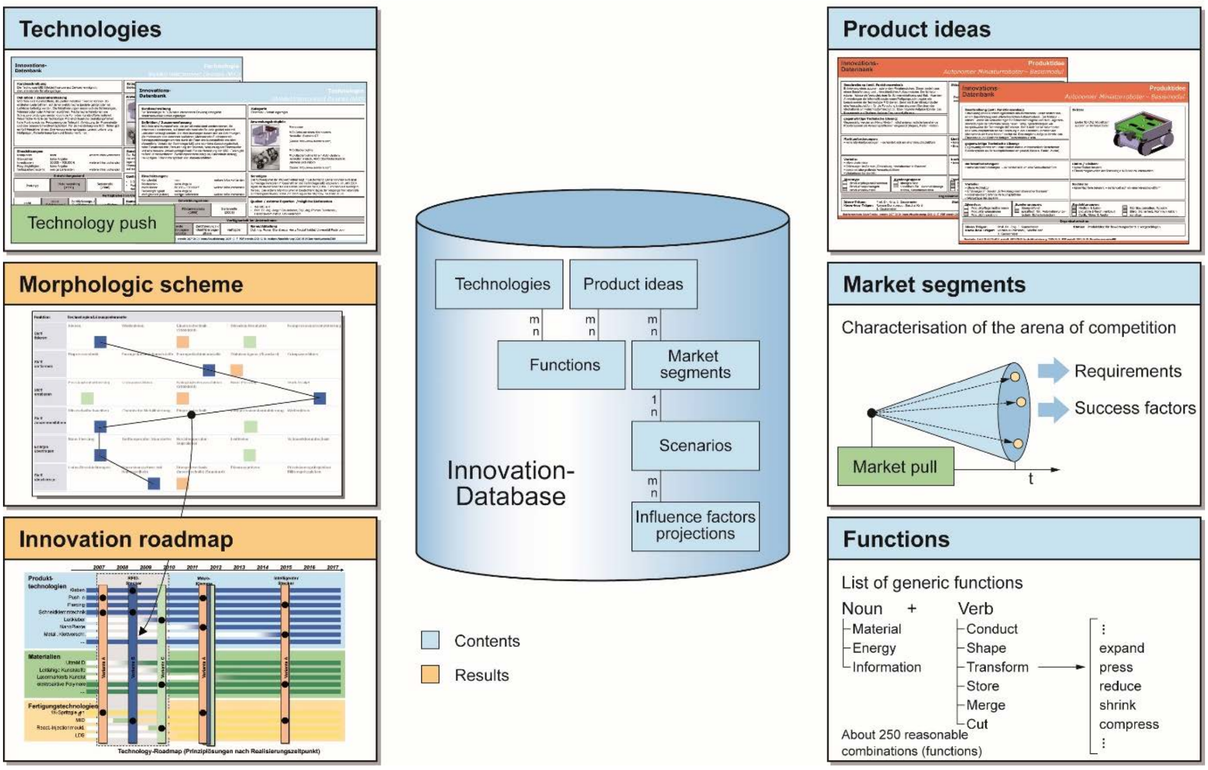

Figure 2: The technology-planning concept of the Heinz Nixdorf Institute – contents and results of the Innovation-Database, Source: Brink et al., 2007

In the following, the relevant entities are explained:

- **Technologies** contain relevant aspects of describing a technology, like a name, description, a graphics and the technology readiness level. It also contains information which technical functions are provided by the technology. Examples for a technology are *radio-frequency identification (RFID) or near field communication (NFC).*
- **Functions** describe the technical functions a product fulfils. Every function can be formalized in form of standard function. Standard Functions consists of a noun (material, energy, information), a main-verb and a sub-verb (Birkhofer, 1980), (Langlotz, 2000). Functions can be delivered by technologies and are demanded by product ideas in order to fulfil a market service.

- **Product ideas** contain relevant aspects of describing innovation ideas, like a name, description, requirements and meta data like the creator of a new idea. The product idea is connected to technologies by describing the product idea with functions.
- **Market segments:** contains all the important information about the market segments, which are derived from the scenario technique. The information can contain the market volume, the estimated growth of the market and further information about market and the environment of the market segment.

The results of the technology-planning concept are also illustrated in figure 2. On the one hand, a morphologic scheme is delivered by analysing which technologies are suitable for building this product. Technologies are suggested by the relational connection of technologies, functions und the product ideas. Within the morphologic scheme, the user is able to choose between different principle solution variants. On the other hand an innovation roadmap is provided, which illustrates every principle solution variant with the planned technology and the estimated technology readiness level.

To use this powerful tool properly it is necessary to have a minimum amount of technologies in the database. As described above, technologies are needed to create the morphologic scheme and the innovation roadmap. Besides a manual filling of the technology pool, which is very extensive, it is possible to use the World Wide Web to collect technologies. There already exist tools for technology intelligence like Mapegy, Idea Connection, Illumin8, Inova and HIS Goldfire. These tools can only be used as a stand-alone solution and support only one aspect of our concept of strategic technology planning. There is a lack of information whether it is possible to export data from those tools.

As already mentioned before, we need a tool, which supports the holistic approach. For that reason, we developed a technology intelligence tool, which is fully integrated in the technology-planning concept of the Heinz Nixdorf Institute. In the following, the technology intelligence process is described.

TECHNOLOGY INTELLIGENCE PROCESS

There are several approaches in literature, which describe a strategic intelligence process (Haertel, 2002), (Lichtenthaler, 2002), (Wellensiek et al., 2011), (Bullinger, 2012), (Gausemeier and Plass, 2014). Some of them are generic for strategic tasks and some are specific for technology intelligence. Nevertheless, all of them are similar. They mainly consist of the definition of the information demand, the description of information acquisition, the evaluation of the information and the decision how to communicate the decision or how to use it in the entrepreneurial context.

In the following, the strategic foresight process by Haertel is used and adopted to technology intelligence. The process model is illustrated in figure 3 (Härtel, 2002). It was re-illustrated by GAUSEMEIER and PLASS (Gausemeier and Plass, 2014).

This process model is cyclic and consists of the following seven tasks:

1. **(Re)-Definition of search fields:** In this task, the search field for technologies is set. This search field has to be delivered by the user and is used as a search criterion in the technology intelligence tool. *Communication technologies* is an example for a search field.

2. **Scanning:** This step describes the non-directional search for new information. In this context, we perform our technology search by using a web crawler and a text mining approach to identify technologies within unstructured data.
3. **Filtering, Formatting, Understanding:** In this step, the information is prepared and additional information, like a short description, is added. Afterwards the information is illustrated to the user. Additionally we add the amount of patents and publications to a technology. This can help the user to estimate the technology readiness level.
4. **Monitoring:** Within this step, further information for a technology or a technology search field is collected over a defined period. It is interesting to monitor performance parameters over a certain time span to get a feeling on how fast the development of that technology is.
5. **Focussing:** In here all the collected data is aggregated and summarized. It is important that all information is available to get a holistic view over the search fields.
6. **Reporting:** The technologies have to be evaluated and chances and risks for one's business have to be derived. It can also be analysed if there are new business opportunities by the found technologies / performance parameters.
7. **Stopping and definition of measures:** In the last step, the technology intelligence process can be stopped and measures can be defined. If there are new insights to adjust the search field, this information can be used to start a new cycle in the process.

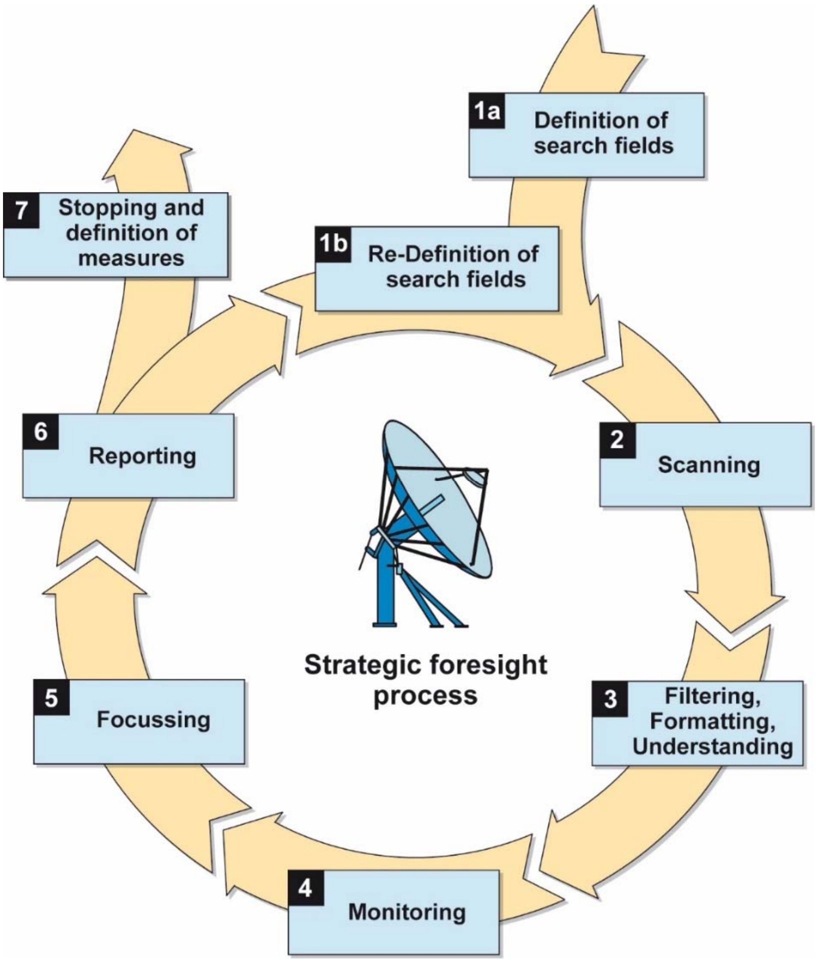

Figure 3: The ideal strategic intelligence process, Source: Gausemeier and Plass, 2014

In this paper, we focus on the information acquisition process, the scanning, the filtering and the formatting of information (steps two and three). The software tool supports these two steps. Afterwards the found technologies are saved and can be used in the Innovation-Database.

Text Mining

Text mining belongs to the field of data mining, which describes the systematic usage of statistical methods to get new insights in the analysed data. This can be used for identifying technologies in texts. To understand the term text mining and define the scope of it, it is necessary to define the difference between structured, semi-structured and non-structured data (Abiteboul et al., 2000):

- **Structured data** has a strict data model, as it is usual in relational databases. It is possible to identify data by the column and the ID of a data set. Each column has a defined data type.
- **Semi-structured** data does not have a strict data model but contain meta data, which tags or categorize the data.
- **Non-structured data** does not have any data structure like natural texts. Words in texts are not categorized so that the computer does not know the meaning of a certain word. Especially in the World Wide Web, most of the data is unstructured.

Text mining contains different methods to transfer non-structured and semi-structured data to structured data in order to allow a further process of the data in order to get new insights. In accordance to MINER, figure 4 illustrates the wide range of text mining methods (Miner et al., 2012).

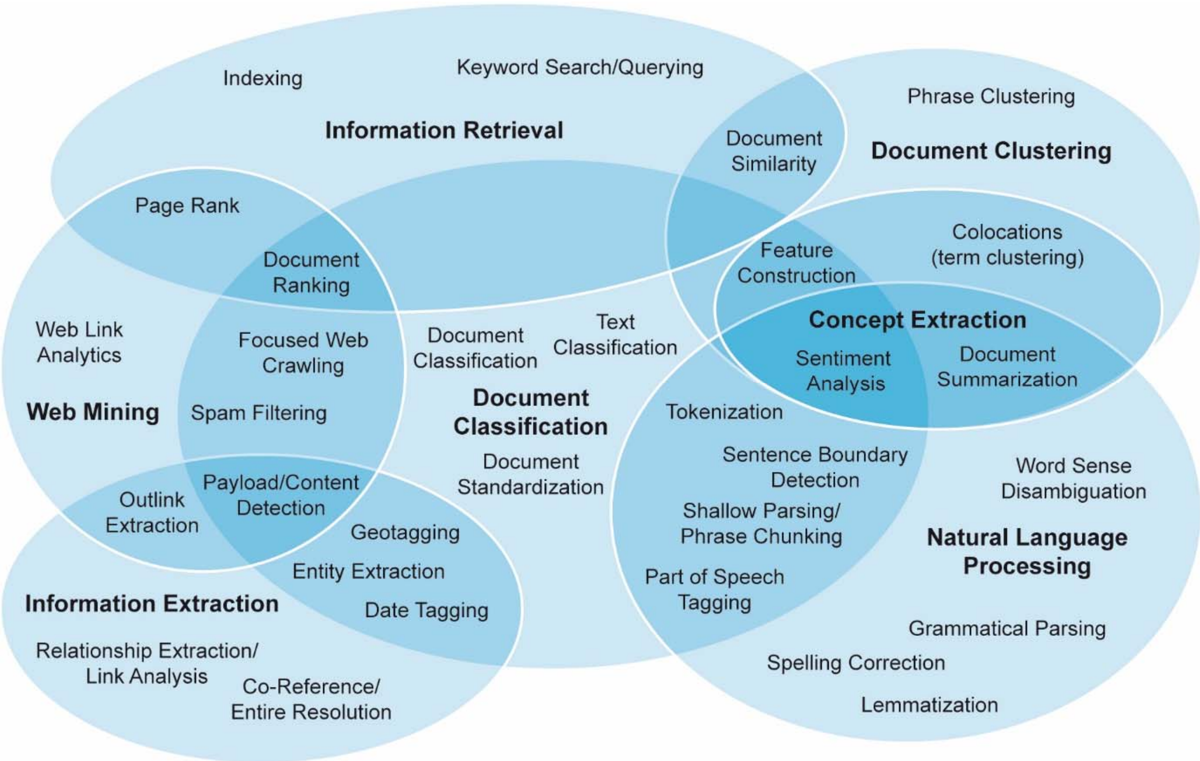

Figure 4: Overview over text mining methods, Source: Abiteboul et al., 2000

The concrete usage of text mining depends on the aim of it. In any case, it needs input data, which is called a document. This can be a single document or a document collection. This document is preprocessed, in which stop-words (i.e. “the”, “and”, etc.) are deleted and a so-called stemming is performed. Stemming means that all the words are transformed to their stem form. As an example, nouns are transformed to its singular form and verbs to the present tense. The complexity of pre-processing is highly adjustable but in any case, the complexity depends on the chosen language. We recommend to use English language because in this language a lot of dictionary exist, which are usable for the pre-processing, like stop-word dictionaries.

For identifying technologies in texts, we mainly use methods of the field of natural language processing and information extraction. These methods provide opportunities to pre-process natural texts and determine the semantic of a word. Concrete, we use a *named entity recognition*-model, which detects certain information in a natural text, like a person, an organization or a location. This concept is derived to find technologies.

These methods can be found in any proper data / text mining-tool like Rapid Miner or KNIME. We use KNIME because of its big community which provides plenty add-ons for text mining. In the following chapter, it is described in detail, how to use these text mining-methods and tools for technology intelligence.

TECHNOLOGY INTELLIGENCE TOOL

In the following, a software tool is described, which uses text mining-methods to detect technologies in natural texts. It is not suitable to scan a text for a defined set of technologies in a dictionary in order to find new ones. With this method it is also not suitable to detect weak signals for technologies. Our software tool finds new technologies for a search field dynamically.

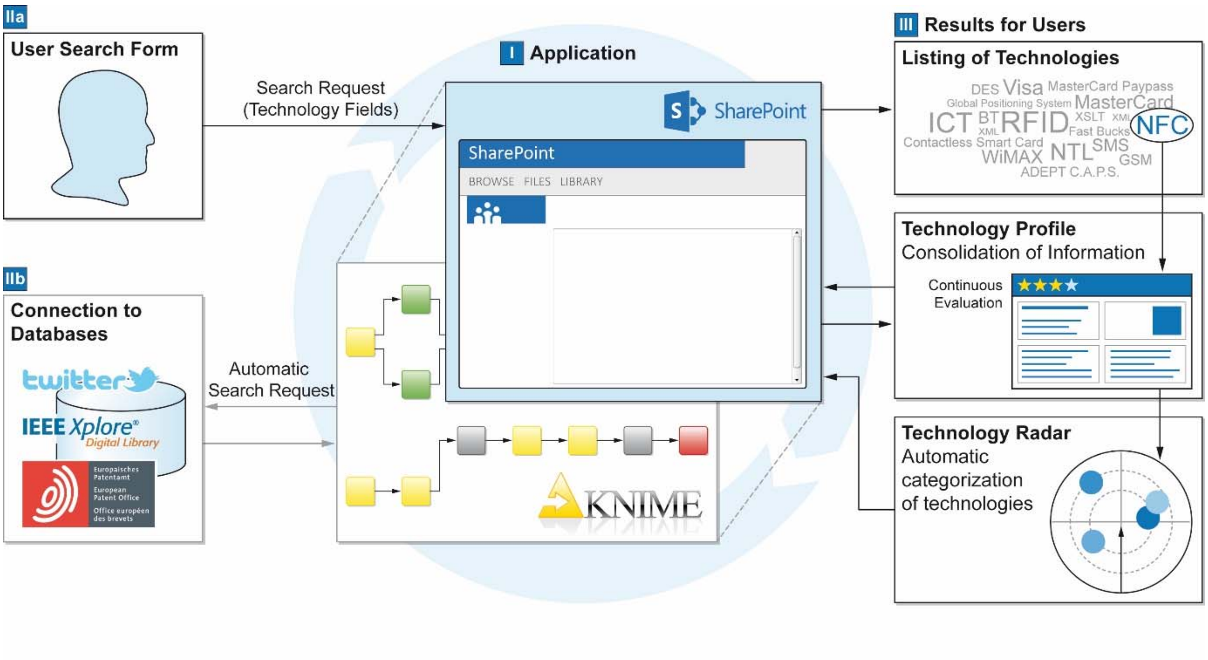

Figure 5: Overview of input and results of the technology intelligence tool

Figure 5 illustrates the connection between input data in form of search fields and data sources and the results for the user. This connection is provided by the application, which is shown in part I. The application is built with the Microsoft SharePoint platform and KNIME Information Miner. The user has to provide a search request in form of a technology field (part IIa). Based on that, the application gathers information from various databases (part IIb). The found information is then processed and finally presented in form of a technology list, technology profiles and a radar view (part III). Each of these parts are described in the following sections.

I – The application

In this section the architecture of the technology intelligence tool is described. This architecture is shown in figure 6. The three main components are based on SharePoint, KNIME and OpenNLP.

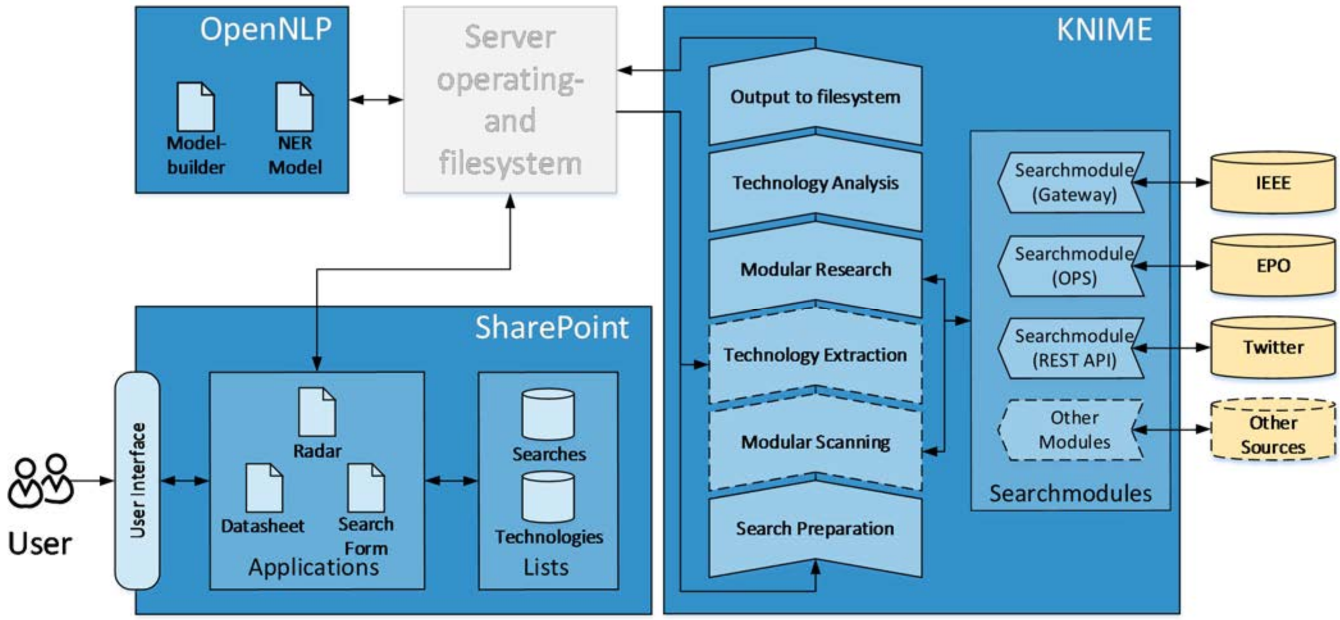

Figure 6: The basic system architecture of the technology intelligence tool

Microsoft SharePoint is used as a platform for interacting with the user. In addition to that is used as a data storage for technologies and all results are presented on that platform. This can be achieved with any other platform with similar features. KNIME is the data mining-tool which we use for text mining. This includes the crawling of data as well as pre-processing of it. OpenNLP is an open source natural language processing tool, which contains a named entity extraction model. We use it for the semantic extraction of technologies.

Since there are no direct interfaces between these components, the operating and file system of the server is used to exchange data and information between those components. For that an appropriate user authorization is needed.

The tool is built in a modular form, consisting of a datasheet, a radar and a search form application. Each tool can be accessed by the user interface. All data is stored in SharePoint lists. Besides technologies also the search requests are stored. This is important for saving computation time if the same request is performed in the future. Each application can communicate with KNIME through the operating system. When the user decides to start a new technology search, a system command is called to execute the KNIME search workflow. Through the command, KNIME will receive the search field as a parameter and performs the technology search. This process is described in the following section in detail. The modular scanning and modular research (monitoring) communicate with search modules. These establish the communication to data sources and provide the raw data, which is analysed. These modules can be extended easily.

The OpenNLP module consists of a model builder and the NER model. The model builder uses example data to build a new statistical NER model for identifying technologies. This model is used by KNIME to query against it. Whenever a new technology is found, the example file and the technology is provided to the model builder in order to recalculate it. This established a continuous machine learning process. This means that there will be an improvement of recognizing new technologies as the users evaluate more search results.

Process for Technology Intelligence

The process for technology intelligence describes the single workflows, which are performed in the KNIME module. Figure 7 shows an overview of this process.

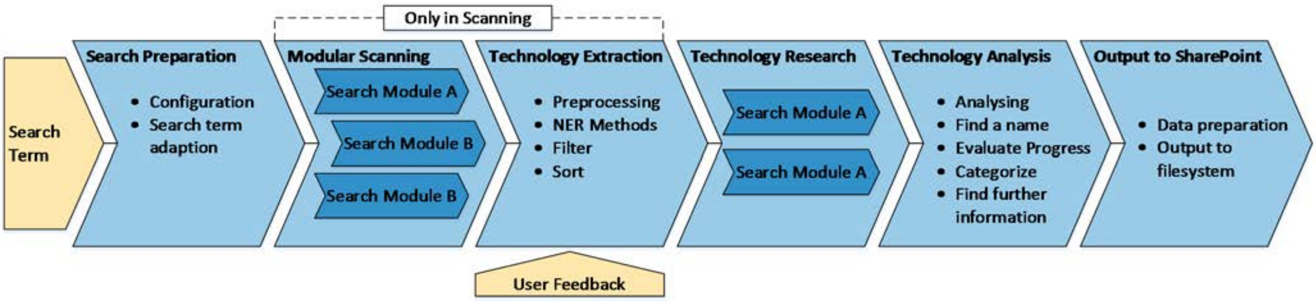

Figure 7: Overview of the technology intelligence process

The process depends on the purpose of the search. For scanning, all process steps have to be done, for monitoring the modular scanning and technology extraction is skipped. The search preparation for monitoring is trivial because it the name of a selected technology as input. For scanning and monitoring different search modules can be connected. Afterwards a technology analysis is performed to provide automatically further information for a technology. All the data is stored in the file system and transferred to the SharePoint application.

In the following the modular scanning and technology extraction is explained in detail. These steps are important for identifying new technologies in unstructured data.

Modular scanning

Figure 8 shows the sub-workflow in KNIME for the modular scanning of this tool. This module initially receives the output data of the search preparation, in particular the adapted search terms chosen by the user. In the next step, search modules are utilized to query the database Espacenet, IEEE Xplore, as well as the social network Twitter. The search modules in this prototype use the search term as input and perform full text searches on these sources. The search delivers different data formats. IEEE Xplore and Espacenet results are based on XML files. These differ in their inherent structure. The Twitter module delivers related “Tweet” text messages and metadata as a KNIME table. Since the data is presented in different formats and structures, it is necessary to reformat the data in a uniform way.

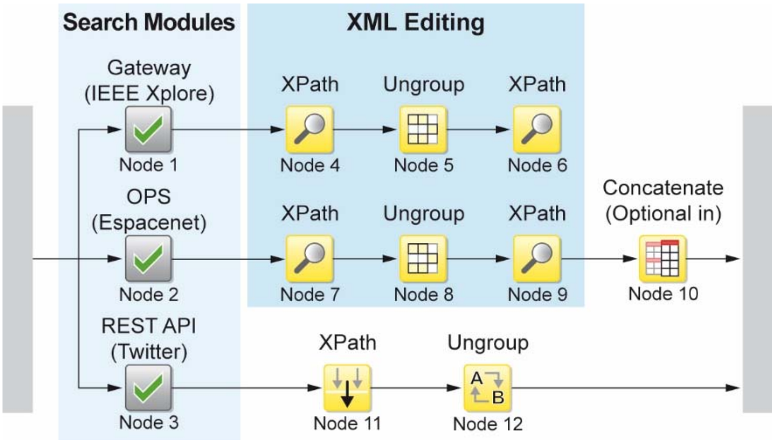

Figure 8: Modular scanning process

XML documents are attributed to each search term. These contain information on patents and scientific publications. In particular, they contain the abstracts of these documents. XPath nodes are used to perform queries on the XML documents. The XPath nodes 4 and 7 extract all the abstracts from each source as single XML elements. Afterwards, the ungroup nodes 5 and 8 separate the found abstracts. Finally, the texts of the abstracts are extracted as strings through the XPath nodes 6 and 9. Every abstract is still associated with the original search term.

The search engine for Twitter directly delivers the texts of every detected Tweet. Redundant data is removed and the formats are normalized through the column filter and ungroup nodes 11 and 12. Afterwards, only the natural language texts with the association to the original search term remain. This way, all the data of the different modules has the same format and structure. New search engines have to be added parallel to these modules. Then the data is processed analogously.

Through the concatenate node 10, the processed data of the search modules is put together. Thus, the modular scanning is completed and the data forwarded to the next step, the technology extraction. This prototype focuses its search on English language texts. Other languages have to be adapted. The source language plays an important role in the technology intelligence process and must be considered throughout its entire process, especially when search modules are added. Searching French texts in a tool that expects English, might lead to unexpected results.

Technology Extraction

As illustrated in figure 7, the technology intelligence process continues with the technology extraction, when the modular scanning is finished. Figure 9 shows the KNIME workflow of the extraction.

The input of this process consists of the search terms and the natural language texts that were found during scanning. The texts contain the collected abstracts and Tweets. In order to process these texts further, they are converted into documents, which is a format that is commonly used by text processing tools. Besides the original texts, the documents contain metadata like title, author and type. This metadata is often needed for various NLP processes. However, those are not necessary for the natural language processing used in this prototype. During the conversion, the metadata columns are filled with dummy data, so that the document format can be used. The string-to-document node is responsible for the conversion.

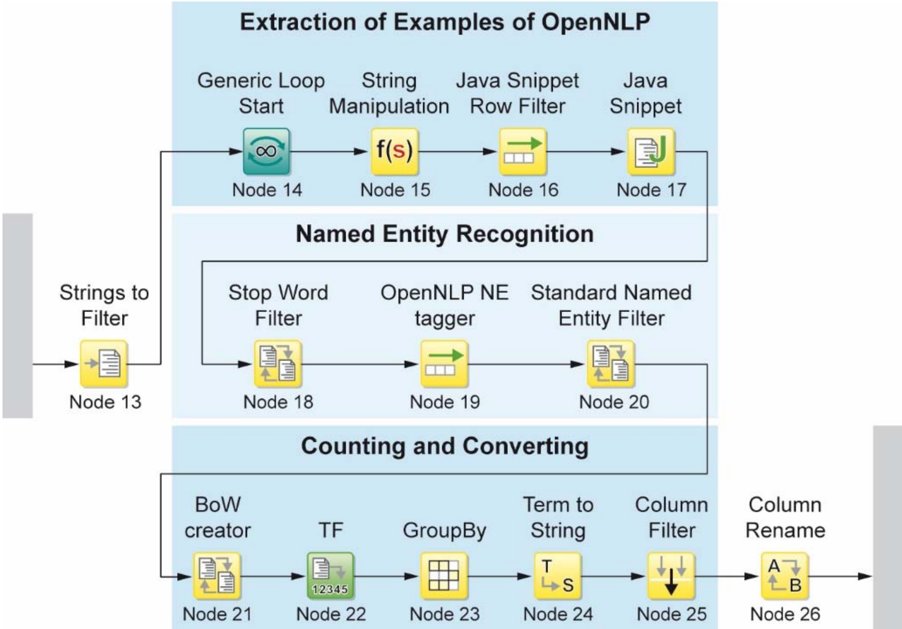

Figure 9: Process of technology extraction

The documents, which now contain abstracts and tweets, are processed in the following steps. In the first steps, example sentences are extracted from the documents, to be used by the OpenNLP learning tool. This tool requires examples of sentences and identified terms to train a model that can recognize a specific category of terms. In this prototype, the sentences are extracted from the abstract data, since Tweets are usually less structured, in terms of natural language. During the extraction the full texts are simply split into sentences and then filtered, so that redundant or unqualified sentences are removed. This may include sentences that are too short or contain special characters. Finally, the sentences are written into a file by the java snippet node 16. The OpenNLP model builder tool (node 17) uses this file in combination with the technologies that are identified through user feedback and build a model for the term extraction.

After that, the named entity recognition of technology names is performed. First, stop words are removed from the documents by the stop word filter (node 18). It exists is no general list of stop words, because it depends on what analysis is being done. In this prototype the standard KNIME stop word filter is used to filter English stop words from the documents. In the next step, OpenNLP Named Entity tagger node is used to tag terms within the documents texts that might be technology names. This node uses the OpenNLP model that is created by the model builder in node 17.

The OpenNLP NE tagger marks the identified technologies within each documents. These terms are extracted and their frequency computed. In general, it is possible to use different measures at this point to calculate a "relevance" for each identified term. This prototype simply uses the term frequency over all documents to determine how relevant a technology name might be in the context of the search field. Finally, the data format is post-processed so that it can be used in the next process steps. The data now contains the original search term, the found technology terms and their respective frequency. The data is sent to the modular research process, in which the most relevant terms are selected for further research.

IIa – The search mask

Figure 10 shows the user interface, in which a user can start a new technology search. It is functional and contains only a textbox to specify the search field and another textbox to indicate how many of the found results are analysed in depth. After the tool has scanned its sources for technology names, the most frequent technologies are analysed and further information is attached.

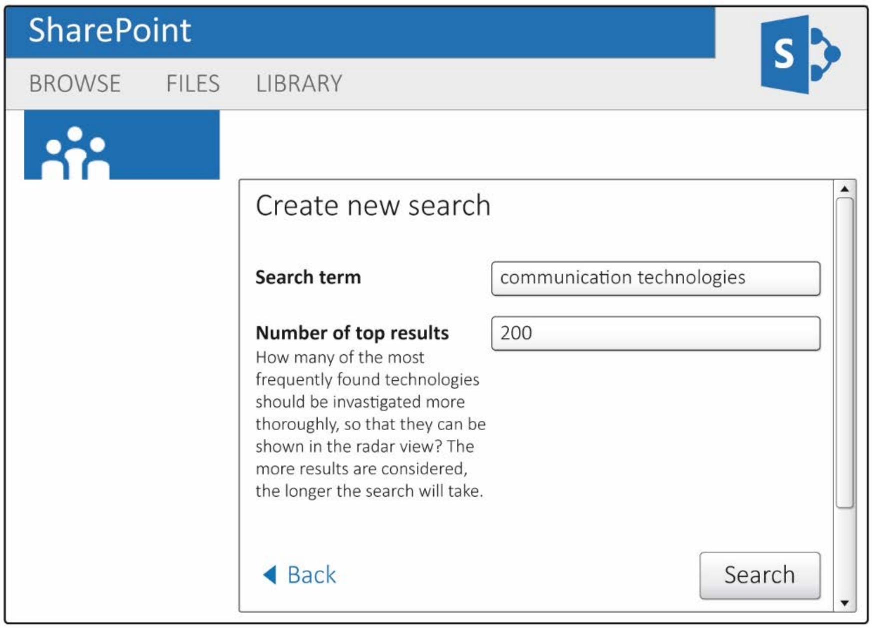

Figure 10: Screenshot of the search mask

IIb – Data sources

Since the application uses search modules to gather data from online databases, the specific sources are interchangeable. For the prototype of the application, three example databases were chosen. This subsection will introduce these sources briefly.

Twitter is a social network, that enables its users to communicate over short messages called 'Tweets' that have a length of no more than 140 characters. Users can choose to follow other users, so that they are notified whenever the latter posts a new message. Since its creation in 2006 Twitter has become one of the largest social networks in the World Wide Web, with about 288 million monthly active users and 500 million Tweets per day (Twitter Inc, 2015). Since trends and news spread very quickly over Twitter and other social networks, some Tweets may contain valuable information for technology intelligence. Furthermore, Twitter has the advantage that all user posts are publicly visible, while on other networks like Facebook, user posts are often only visible in certain groups. For these reasons, Twitter was chosen as a data source for the prototype and is queried automatically by the application.

The Institute of Electrical and Electronics Engineers (IEEE) is one of the largest associations of professionals in the field of electrical engineering and information technology (IEEE, 2015). The IEEE regularly hosts conferences and publicises articles and papers on technological topics. They also offer the IEEE Xplore service that enables users to access many of their scientific publications online. Such scientific articles may contain important information that gives insights into new technological developments. The database is therefore queried by the prototype to extract especially abstracts and meta-data from articles related to a search term.

In some cases it may take some time until a scientific paper is published on a new technological development. However, patent documents may contain information on developments at an early point of time. According to some studies, patents contain 80% of all technological knowledge (US Patent Office, 1977). Patent analyses are often used in technology intelligence. The European Patent Office (EPO) offers their online database Espacenet to access the information of over 80 million patents. The prototype uses the Online Patent Services interface to query the database.

III – Results for the users

The results for the users are offered in three different ways. A listing of the found technologies, a technology profile and a radar is implemented. These parts are explained in the following subsections.

Technology list

The data model of the technology intelligence tool is implemented by using SharePoint lists. These are illustrated by the names “Searches” and “Technologies” in figure 6. The “Searches”-list contains metadata for all technology searches that have been conducted, such as the search term, the date etc. Each of the list items in the “Technologies”-list contains a field referring to an item from the searches list. This way, each of the found technologies can be assigned to a certain search. Furthermore, the technology list items contain a number of data fields that describe the technology. Most important, they contain a text field that allows users to describe the context of the technology in regards to their own company. Table 1 shows an example list of found technologies using the search field “communication technologies”. “Row ID” is an unique identifier of that list, “Frequency” shows the amount of times, which this term was found in the example set and “Technology” describes the name.

Table 1: Example of the most relevant found technologies for the search field “communication technologies”

Row ID	Frequency	Technology
Row85	36	radio-frequency identififaction
Row86	33	near field communication
Row88	32	bluetooth
Row18	30	continuous wave
...	...	...

Technology Profile

Figure 11 illustrates an example of a partial technology profile. Besides the name, a description the search term is shown. Furthermore, the profile may contain bibliographical information, pictures or links to technical documents, which is not illustrated in this figure. The profile gives the user the option to add a personal assessment of the value, the technology has. The user can also modify other information or initialize a thorough research for a single technology. It is important that the user rates this term whether it is actually a technology or not. This user feedback will trigger the machine learning part of the software and help to identify technologies even better in future searches.

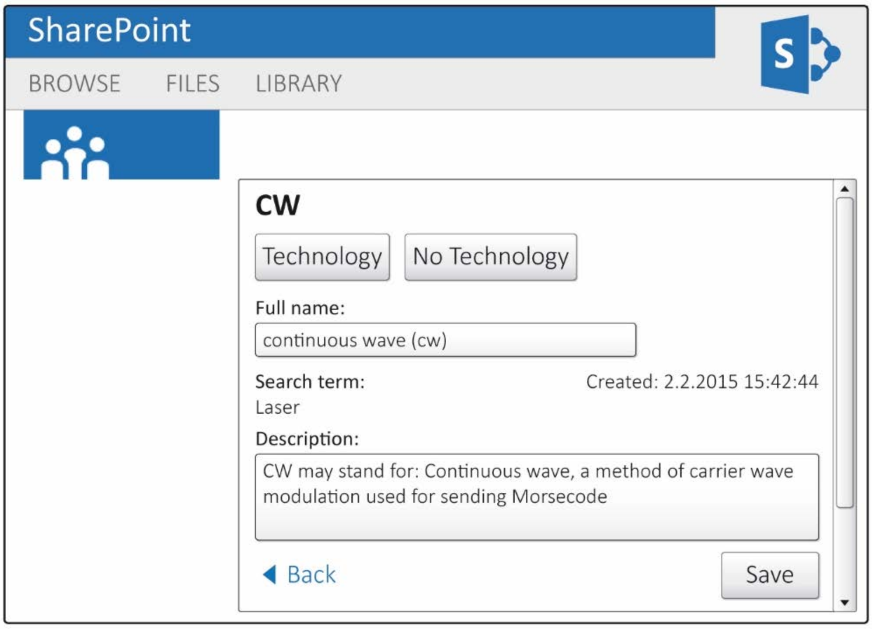

Figure 11: Screenshot of the technology profile

Technology Radar

The last result is a technology radar. An example of such a radar is shown in figure 12. This visualization gives the user an overview of the relevance and impact on the business model of each technology. There is also an automatic categorization, which is shown in the segments of this radar.

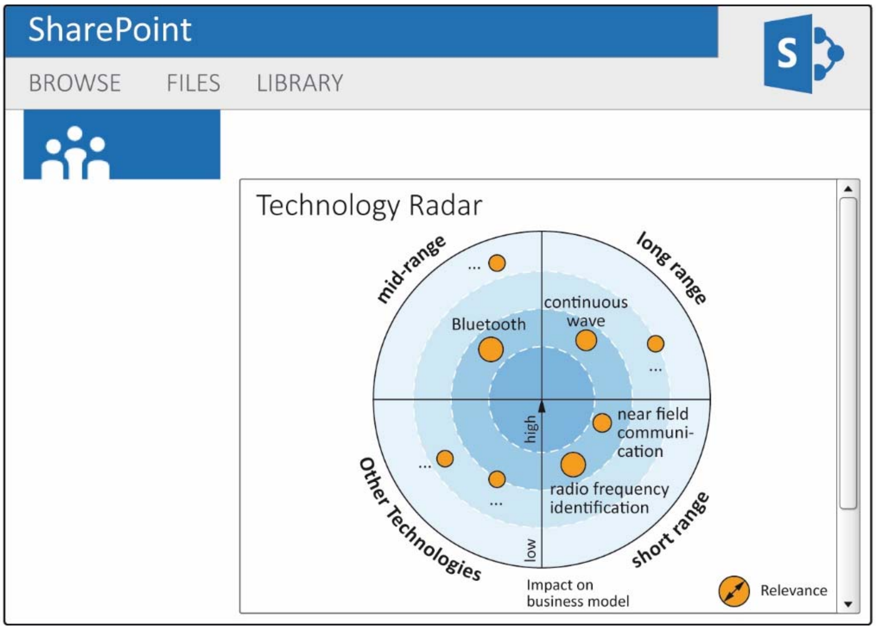

Figure 12: Screenshot of the technology radar

The radar screen is split into four section. Each section represents a category in which the technologies are assigned to. The size of the circle indicates the relevance of the technology. Furthermore, the radar screen shows concentric circles of different size and colour. These zones illustrates the impact on the business model of the respective technology. The closer a technology is arranged to the centre, the higher the impact. This arrangement can be customized easily. As an example, the concentric circles can be defined as the maturity level of a technology. Technologies, which are farther away from the centre of the radar, are only in the beginning of their technological development. Technologies close to the centre are either already developed or are rapidly developing. The tool provides as much information as possible in order to support the user to evaluate a technology.

After a technology is evaluated concerning its relevance and the impact on the business model, it is arranged automatically in the radar. In this example, communication technologies were found and categorized into their radio ranges.

CONCLUSION

For strategic product and technology planning, a holistic process and tool is needed to support a company in the innovation process. Therefore, the technology planning-concept and the Innovation-Database from the Heinz Nixdorf Institute was used as a knowledge management system. The challenge is that the technology pool has to be filled with a minimum set of technologies in order to use the whole functionality of the Innovation-Database. A manual continuous filling of the technology pool is a big problem. Therefore a software tool was built, which automatically identifies technologies in defined data sources. Furthermore, it automatically prepares the data and visualize it in the tool. As input data, natural texts from the European Patent Office and the IEEE Xplore are used. It is not suitable to compare those texts with a given dictionary of technologies. New technologies and weak signals cannot be found with this method. Because of that, we used text mining-models to identify by using statistical methods. The results are visualized in different ways. A list of technologies is provided for the user to get an overview of the search results. The user has to evaluate each technology by using the technology profile. After that the technology is visualized in a technology radar.

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