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Data-Driven Technology Management Supported by Artificial Intelligence Solutions

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Abstract

Technology Management is an important part of a company's business strategy. Procuring, evaluating, and processing information is crucial for this process' success. This paper describes the way of dealing with today's challenge of information overload. It introduces a concept of technology databases based on opportunity evaluation and the systematical development process of technical systems. The idea is to capture two perspectives – generic technology information outside the company and internal technology knowledge – in one comprehensive database to be used as a basis for decision-making in technology management. Complementing this, the paper presents concepts of Artificial Intelligence-based information retrieval and processing that are suitable to efficiently support and semi-automate the filling and updating of such a database. Furthermore, existing software solutions are considered as exemplary. The finding of this paper is a combined approach of such a technology database with artificial intelligence methods for information retrieval that can support the process of technology management more comprehensively than is currently possible.

Keywords

Technology Management; Technology Database; Information Retrieval; Artificial Intelligence

1. Introduction

Social, economic, and societal change, which has become dominant due to a wide range of technological developments, affects small and medium-sized as well as large companies. These companies are faced with increasingly rapid changes, shortening product cycles, and growing competitive pressure, i.e., with increasing complexity and dynamics. According to SPATH ET AL [1], the triad of knowledge, willingness and ability forms the basis for economic success. Knowledge has thus become the new raw material [2]. To survive in this environment, the ability to master and further develop technological innovations, and to manage the current and future technology inventory in a targeted manner is essential. With that in mind, technology management is becoming more important [3]. The successful management of this process secures the important resource of unique technology know-how, allows the performance characteristics, competitive impact, and customer benefit of these technologies to be correctly assessed and used. Furthermore, by performing strategic foresight it ensures that new trends and technological developments can be identified at an early stage and correctly assessed in terms of opportunities and risks for the company.

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Beyond that, the pace of technological progress speeds up exponentially over time [4], while companies must keep pace with these developments. Although access to necessary information is easy in the information age, it also leads to information overload.

Between 2006 and 2015, the Google index temporarily contained up to 49.4 billion documents [5], the overall technical information storage capacity reached 295 optimally compressed exabytes or 404 billion 730-MB-CD-ROMs in 2007 [6]. The number of published research papers passed 50 million in 2009 [7], in 2015 the number of yearly published articles in scholarly peer-reviewed English-language journals was estimated to 2.5 million [8]. The U.S. Patent and Trademark Office recorded nearly 400.000 patent grants in 2019 [9].

Looking at these numbers, it is evident that this amount of information can no longer be fully observed and evaluated manually. For this reason, today's technology driven companies need meaningful technologies for information retrieval and processing in addition to appropriate technology management strategies and processes to cope with this development to stay ahead of the competition. This addresses the need of using capabilities to early detect upcoming technologies and evaluate opportunities and threats for the company's business [10]. Also, in this regard a well set up and integrated technology management process run by engaged technology managers are key for the long-term success of companies [11].

This publication initially summarizes the theoretical basis to structure the general technology landscape, which includes all existing technologies, to organize technology management, and to automatically retrieve and process information. Building upon, existing software tools and services to support these activities are discussed.

Afterwards, the paper introduces a comprehensive approach of a data-driven technology management based on TCB/SETS databases and supported by suitable artificial intelligence (AI) solutions. Finally, this approach is discussed and compared to the previously mentioned, existing solutions.

2. Theory

The approach to support technology management is based on automated research process and data management assistance. This chapter introduces proven practices and methods, which serve as a basis for our considerations, and examines existing software tools.

Initially, the complexity of the general technology landscape is discussed before the structuring approach based on BULLINGER [12] is presented. Then, the text introduces technology management and its underlying processes and activities as important part of a company's business processes according to SCHUH [13] and KLAPPERT ET AL [14]. Regarding the approach presented later, this chapter especially examines technology strategy, intelligence, and assessment, because they are suitable for motivating, aligning, and continuously expanding a fundamental technological knowledge base for a company. Afterwards, the focus is on artificial intelligence and its possibilities and limits to support data- and knowledge-based processes. Specific methods are introduced, which are meaningful to be used in technology management for the purposes of information procurement, classification, and assessment. Furthermore, types of software tools intended to support technology management are examined. Exemplary for the different types, some of the solutions available on the market are presented. Building on these theoretical foundations, the approach gets introduced and discussed.

2.1 Structuring the Technology Landscape

The complexity of the general technology landscape continues to grow at a high rate, and this across all industries worldwide. It is characterized on the one hand by its enormous breadth and depth, and on the other hand by the diverse networking aspects between the development paths of different technologies as well as the different perspectives of politics, society, economy, and science.

An example how to structure the technology landscape is given by BULLINGER [12]. This example divides the technology landscape into technology fields, technology families, and the related individual technologies. This concept can still be used as a guideline for the structuring of technologies today, as shown in figure 1, although many new technologies have emerged and will continue to emerge.

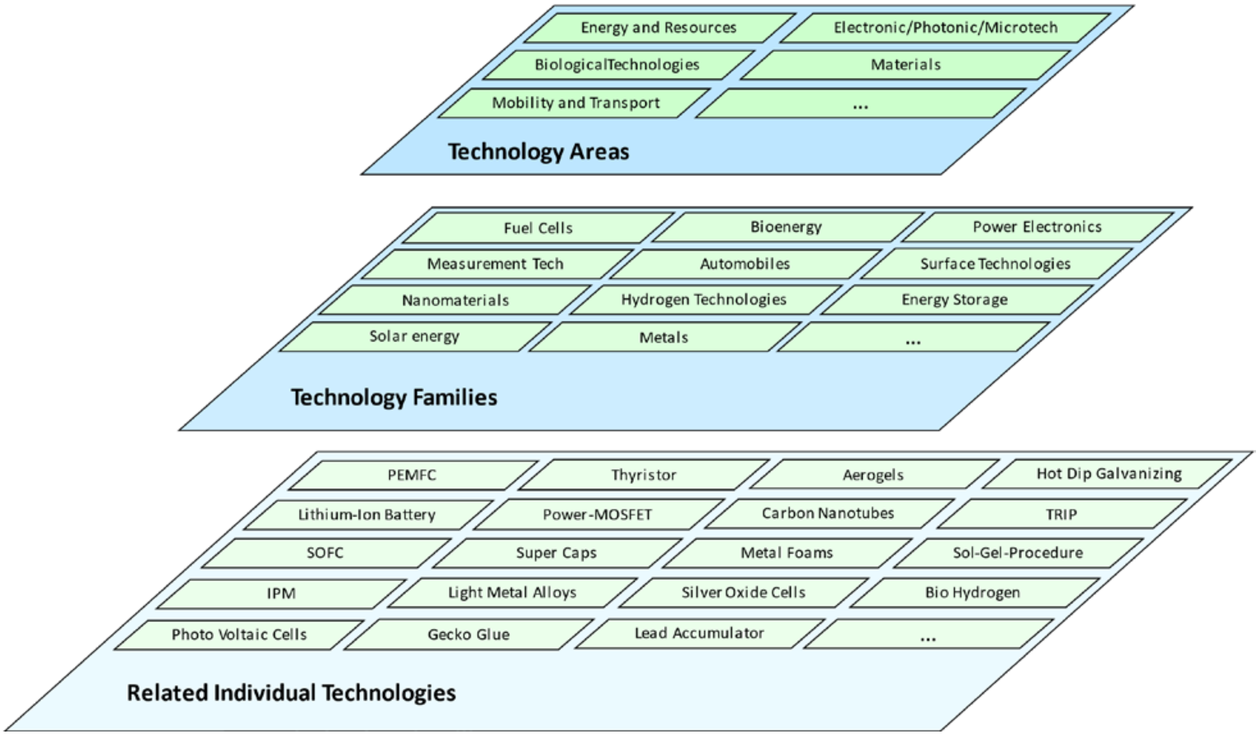

Figure 1: Technology landscape as used in the TCB structure, based on BULLINGER [12].

An indicator for this rapid development of technologies is the large amount of information that is generated worldwide in the form of patents, publications, etc., and which is important for companies as well as for nations to follow up with, as already mentioned in the introduction. One reason for the increasing amount of technology information is, as BULLINGER [12] points out, the increasing speed with which knowledge from research and science is transferred to the development of products and to their production. E.g., results from nanotechnology and artificial intelligence are already used in many fields of application, although these are relatively new technologies and further research is needed.

In companies, the ability to ensure innovations through technological development is the task of technology managers. Among other things, it is their task to recognize the opportunities and risks of new technologies and their effect on the company's product portfolio at an early stage, and to systematically determine the corresponding need for action. This leads to the process of technology management, which will be introduced in the following.

2.2 Technology Management

SCHUH defines a framework for production and management [13] based on Rüegg-Stürm [15], in which technology management is embedded as business process of a company. The framework shows how important it is to see technology management as part of the overall business context, and accordingly the technology strategy as part of the corporate strategy. According to SCHUH ET AL. [16] these basic activities of technology management are formulated:

- **Technology Intelligence** creates a transparent information base to support strategic decision-making processes in the company and acts as a link between strategy formulation and technology planning [17]. The aim of this early detection is to provide relevant information about changes in the entire environment of the company to identify potential opportunities and risks at an early stage.
- **Technology Planning** includes the determination and systematization of all activities, processes, costs, resources, and deadlines and represents the mental anticipation of future actions [18]. In industry, road-mapping is widely used as a method for implementing technology planning [19].
- **Technology Development** aims to efficiently implement the specifications of technology planning. The formalism of the process is essential to create transparency and to prepare a decision for technology planning [20].
- **Technology Exploitation** is differentiated between internal and external exploitation. Internal exploitation focuses on the use of unique technological capabilities in the company's own products with the aim of gaining a competitive advantage. External exploitation by third parties takes place to increase the profitability of a technology investment and to help maximize the economic benefit [21].
- **Technology Assessment** is part of all stages of technology management. High performance in technology assessment is an important, cross-phase prerequisite for the efficient and effective design of technology management [22].
- **Technology Protection** aims to protect proprietary technological knowledge from being transferred to competitors by developing sophisticated protection mechanisms. These prevent or at least make it more difficult to imitate technologies and products [23].

In fulfilling these tasks, information usually has to be collected and evaluated, and in doing so, it is important to handle the high amount of data in a reliable manner and to prepare it in a targeted and clear manner according to the requirements. In the further course of this article, the focus is on the general technology strategy and on the activities of technology intelligence as basis for motivating, aligning, and continuously expanding a company’s technology knowledge, so in the following they are presented in more detail.

2.2.1 Technology Strategy

Technology strategy is a central element of technology management. It is designed via the dimensions of technology selection, performance, timing, source, and exploitation. Additionally, it is embedded in a network of corporate, business segment, competitive and functional strategies [24]. The technology strategy occupies a superordinate position because it is the central guideline for all tasks of technology management and accordingly an important part of a company’s business strategy [14].

Technology strategies have individual technologies or technology fields as reference objects. A strategic field of technology can be defined as a section of the current and potential technological field of activity. It is characterized by the fact that it can be planned independently of the other fields of technology. To identify a strategic field of technology, reference can be made to the scientific-technical and the technical-economic level [25, 26]. The technologies of a strategic technology field do not have to be independent of each other. They can stand in a competitive, complementary, or neutral relationship to one another, so that they form a technology platform [24].

To represent such relationships and thus structure technology fields, so-called technology trees are used, in which overarching characteristics of related technologies, such as knowledge content, functions, products and markets are presented in a step-by-step concept [27]. The strategic aspects of technology platforms and technology trees address important requirements for data-based technology management.

2.2.2 Technology Intelligence

As explained before, the technology strategy occupies an overarching position, as it provides a guideline for all technology management tasks. Thus, the technology strategy is also the basis for the systematization of technology intelligence as central point of orientation for the derivation of search fields, the existing or targeted core competencies and the underlying core technologies. In addition, all specifications in the individual dimensions of the technology strategy have an impact on the early recognition of technologies or the need for information [28]. At the same time, the findings of technology intelligence provide crucial information for strategy development. Changes in existing and new technologies may require new approaches that entail an adaptation of the technology strategy.

The early recognition of technology thus represents a component of company-wide strategic business intelligence [29, 30]. The aim of this foresight process is to provide relevant information about changes in the entire environment of the company to identify potential opportunities and risks at an early stage. While technology intelligence is geared to all future developments and events in the corporate environment, as part of these activities it focuses on the analysis and prognosis of the technological potential of new technologies and the determination of the technological performance limits of existing technologies [30].

The objective is to identify developments in relevant fields of technology as a basis for technology decisions in the company. The process essentially consists of the four steps of determining the need for information, obtaining information, analyzing, and communicating it.

Technology scanning, scouting, and monitoring are the basic activities or search perspectives of technology intelligence. All three activities have the common goal of avoiding future technological surprises through a targeted search for information and providing technology management with a basis for making decisions regarding potential technological options for action.

Technology scanning is a continuous, undirected search for information within or outside the domain of a company. The company thus gains a broad overview of possible technology-relevant information, which may also include previously unknown or even completely new aspects [31]. Technology monitoring is linked to scanning and takes a closer look at what is happening in individual technology fields. The developments in specific subject areas are followed in a formalized manner over a longer period, both from a technological and a market perspective. Finally, certain technology topics and corresponding information sources represent the object of observation of technology scouting. This is a rapid procurement of detailed, technology-relevant information in accordance with the contract [32].

The subdivision into three basic activities with a graduated level of search detail serves, among other things, to efficiently design early technology detection. Since a detailed search is very time-consuming, it must be focused on specific information needs [33].

In the run-up to the procurement of information, early technology identification must compare the benefits of the individual information sources with the associated costs. In the end, the information sources that should be used are those that are characterized by comparatively good cost-benefit ratios and thus fit optimally with the search request. The procurement of information therefore always represents a compromise between an almost infinite amount of existing information on the one hand and limited possibilities for its exploitation on the other.

For the targeted and effective use of the acquired information, an appropriate preparation of the findings of early detection is also essential [34]. In practice, the results range from emails, short reports and trend reports to project proposals, analyses, and future studies [35]. The diversity of information in technology intelligence makes it difficult to set standards for its communication and documentation. Overall, too much formalism should be avoided to maintain the necessary flexibility and acceptance in the process. However, content and structural specifications should be specified as a guide for recurring presentations. The choice and design of the appropriate form of presentation follows from the decision-making situation and the available information base. For example, it is advisable for a management summary to present the advantages and disadvantages, a timetable, and expected costs in a compact way and to avoid operational and technical details.

For the communication of technology information, technology profiles are well suited, because they contain the essential aspects in a shortened form to easily transport the most important information. Usually, they contain information on the technologies' principle, advantages, and disadvantages, (potential) applications, and sources of technology and information. Profiles are suitable for comparing technologies and serve as a basis for discussion and decision-making in management. Further information can be stored in technology data sheets, which are structured analogously to the profile but contain more technical details.

Since the findings of technology intelligence can only partially be communicated directly, and since more detailed information must also be available in the long term, they must be stored in a system. In practice, database systems have become established that enable functions such as storage, forwarding and access control.

Such systems are also suitable because of the division of labor and decentralized collection of information [36]. The challenge for the systems is the flood of data and the diversity or unstructuredness of the information [37], which can, however, be solved by new concepts of information systems, such as wiki systems for the individual storage and search of various information. In addition, the repository can also be used to evaluate all information for further aggregation.

IT systems are certainly helpful and necessary to cope with the large and growing amount of information. However, they only serve as support and require proven processes of knowledge management to be effective.

2.2.3 Technology Assessment

Technology assessment refers to the evaluation of a technology against the background of several criteria in different decision-making situations. Within the technology management process, it is therefore a cross-sectional function that serves to provide the necessary information basis in different decision-making situations. Decision situations occur in all phases of technology management that require corresponding tasks and adapted assessment methods [22]. Since the topic of technology intelligence is particularly important for our further considerations, the focus is on this aspect of technology management in the evaluation question.

In this context the assessment of incomplete information is relevant. To supplement missing information, empirical analyses or expert assessments must therefore be used to a large extent. Due to the early development stage of the technologies under consideration, future performance characteristics can only be predicted and concrete information on the application context of the technologies under consideration within the products or manufacturing processes is missing.

There is no precise distinction between the relevance assessment in information gathering ("filtering") and the assessment of the already gathered information. Thus, analysis steps are already taken when the incoming indicators are included, which leads to a reduction in their number.

The evaluation of technologies is based on the whole context which contains criteria and requirements that arise from the different organizational areas of the company and in the following steps of the technology management process. In contrast to further analysis steps, which are necessary in the context of technology planning, an information basis is created here that is largely unbound to the purpose. The following evaluation criteria are relevant in a multidimensional analysis [38]:

– Possible (technical) performance parameters of the new technology
– Prognosis of the expected costs and benefits of the technology option

- Detailed assessment of opportunities (e.g., market/synergy/competition potential) and risks (e.g., implementation/acceptance risks)
- Determining the (strategic) relevance of the technology options for the company
- Estimation of the necessary implementation effort (including financial expenditures for R&D projects, need for assistive technologies, etc.)

The assessment of these criteria is based primarily on approaches of technology forecasting in the sense of predicting the probable development directions of individual leading indicators regarding defined performance parameters. These analysis steps are intended to ensure that only those technology options with the greatest technical suitability and with the best market opportunities, e.g., in terms of a return on investment and the sustainability of the solution are transferred to technology planning phase [38, 39, 40].

The information evaluation phase is concluded by an overall assessment of the information generated. This influences the decision regarding the further handling of the technology in question. It is conceivable, e.g., that in the case of a promising overall assessment, concrete pre-development projects will be initiated, or technological concepts will be examined in more detail before a final decision is made. A clear separation between the information evaluation in technology intelligence and the information analysis in the context of technology planning, which leads to the development of realistic options for action, is not conducive to achieve the desired results. A differentiating characteristic, however, is the purpose-relatedness or the concrete orientation of the analysis results to a specific decision problem situation in technology planning.

2.2.4 Technology Roadmapping

For the implementation of technology planning, technology roadmapping has practically become the standard in industrial practice. This method offers an approach to support the process of technology planning and the coordination of the planning levels considered in technology planning throughout. Roadmaps provide information about current and planned projects, previous decisions, dependencies, and causalities. So, the roadmap supports orientation on complex technology implementation tasks. It is not only possible to determine the current position, but also to clearly plan and display the route to the destination including its intermediate steps and alternative routes [19]. To support the process of technology roadmapping itself, AI-based software solutions are discussed and already provided as a tool or service [41, 42].

2.3 Artificial Intelligence Methods and Solutions

Artificial Intelligence is one of the most popular topics at present, but it is just as complex. One of the current challenges is to be able to assess the existing possibilities regarding the given requirements and to use them in a targeted manner.

Basically, Artificial Intelligence makes decisions based on probabilities, which are determined, e.g., by statistical and stochastic data analysis. As a basis for this analysis, new decisions are made based on experience. For this purpose, the Artificial Intelligence is prepared with training data, which is the so-called Machine Learning process. Machine Learning is not a synonym for Artificial Intelligence, it is a technology to make predictions of the future, and for this purpose, it is used by Artificial Intelligence in various ways [43]. Very complex decision problems, like recognition of individual objects on images, rely on information processing models such as artificial neural networks. Thereto, complex decision systems inspired by the biological neural system are built based on training data, which is called Deep Learning [44].

With reference to the questions of technology management, this paper considers primarily solutions for the procurement, classification, entity recognition, and evaluation of relevant technology information. The focus is on these tasks, since they are suitable in combination to ensure a fundamental compilation and actualization of technology information: The procurement as basic information collection, the classification for the first allocation into existing categories and if necessary for a first relevance evaluation, the Entity

Recognition for the determination of concretely mentioned entities of technologies over enterprises up to individual persons and finally the context-dependent evaluation of the available information on their general quality, topicality, and suitability.

2.3.1 Procurement

As already explained, large and not-manageable amounts of information are available today. In order to make this information usable, it is necessary to obtain the information relevant for one's own application as efficiently as possible. Various archives like arXiv of Cornell University [45], libraries like the Library of Congress [46], and public institutions (e.g., patent offices) provide free interfaces to access their digital data stock in a machine-readable format. Specific requests can be sent to such sources to obtain relevant information. However, the Internet contains much more relevant data in mostly heterogeneous formats, such as the websites of technology manufacturers and providers.

Web Crawlers are suitable for capturing such data. These programs start on predefined starting web pages, so called seed pages, and follow all links to further pages. In this way, Web Crawlers capture the Internet in an explorative way and can, for example, store the contents of all accessed web pages, e.g., for use in a search index to provide a search engine [47].

But capturing all available content is not efficient if only documents relevant to the current topic are required. Therefore, intelligent strategies are necessary to perform information procurement in a targeted manner. Improved Web Crawlers, which can follow a defined topically focus by applying such strategies, are called Focused Web Crawlers [48], or in short: Focused Crawlers. These strategies can be improved pathfinding methods, which take care of selecting the most efficient paths through linked information sources like the World Wide Web, as well as classification, segmentation, and evaluation of the determined information.

2.3.2 Pathfinding

Pathfinding through linked information sources can be optimized by deciding, based on the relevance of the current document, whether it makes sense to follow further links on this page. If several irrelevant pages follow each other, the following of links in this direction is interrupted. This procedure is called Fish Search [49]. A further development of this approach is the so-called Shark Search [50]. Here, the relevance of the following pages is already estimated before they are downloaded, which reduces unnecessary downloads and increases the efficiency of the pathfinding process.

In addition to the relevance of the current document, the context of the link can be examined to choose the next link to follow [51]. If the link is located within a relevant content paragraph, the probability to get further relevant information is higher, whereas a link in the advertising area of a web page can lead away from the topic.

By merging access to existing interfaces and efficiently obtaining further, unstructured information, a relevant information base can be created and processed.

2.3.3 Classification and Segmentation

The processing of textual information via artificial intelligence belongs to the field of Natural Language Processing (NLP). Computer systems are not capable of understanding natural language, but they can convert it into a numerical representation and use this to determine semantic relationships.

Simple text classification methods use the frequency of terms within a document or a document set to assign the text to a content category [52]. More complex methods break down the text into smaller elements of meaning, so called tokens, and encode them as multidimensional vectors. Such an abstract representation of text allows the comparison of semantic similarities between these tokens. This not only includes whether or how often the tokens occur within the text, but also whether they occur in a similar context. Thus, a more precise classification of the text is possible [53]. For example, if the term "letter" occurs, such a method can decide with higher probability whether the term is used in the sense of a character or a mail.

As already mentioned before, the classification of a text is always done in terms of probabilities. The parameters examined in connection with the chosen method finally result in the likelihood with which the present text can be sorted into the known categories. In the ideal case, the likelihood for one category is significantly higher than for the other categories, but uncertainties cannot be excluded. The quality of the classifier is particularly related to the quality and quantity of the training data, i.e., the texts that were initially provided as comparative material for the defined categories. The compilation of this training data requires an initial, manual effort, but is crucial [54]. The extent of this training data depends on many factors, e.g., how selective the categories are, which is why it is difficult to estimate in advance how large the initial effort must be [55].

If no categories are defined at the beginning, or if too little training data is available, there is the alternative possibility to segment the texts. For this purpose, only the number of clusters into which the existing material must be divided is determined. The texts are coded in the same way as they would be classified, but they are not compared with predefined categories, but with each other. By using algorithms like k-Means [56], it is possible to divide the text data into the desired number of clusters of equal size. These clusters can be named and thus used as initial categories.

2.3.4 Named Entity Recognition

Named Entity Recognition is another Named Language Processing method that is used to identify proper names in a text, such as places, persons, or companies. For this purpose, features are defined which the algorithm can use to recognize names. In the simplest case these are word lists, but they also include surrounding words, the position in the sentence or the spelling, e.g., capitalization in English. Based on training data in which names are already marked, the algorithm learns how to apply the features and can thus find already known proper names as well as recognize new names [57]. The results can be used to add keywords to texts, classify them on this basis or analyse their content.

In this way, data can be enriched very quickly and easily with additional information, e.g., about mentioned companies or persons, making it possible to create further keywords and links without complex analysis approaches.

2.3.5 Assessment

By collecting and classifying relevant information, Artificial Intelligence can already make a useful contribution to information processing in terms of technology management. A further, valuable support consists in evaluating the content of the available documents. It is possible to extract from text what linguistic quality it has, what the basic mood of the text is, or even whether the text takes a positive or negative position towards a named technology [58, 59, 60].

While the quality of the collected information can also be evaluated by analysing the tokens or by examining concrete features, e.g., whether the text contains references, an evaluation of the mood or position is more complex. For this purpose, a so-called sentiment analysis is performed, which is comparable to text classification. Using training data about mood and positions, the algorithm can also detect similarities and, on this basis, calculate the probability of a mood or position of the text or individual statements within the text [61].

A difficulty in such an analysis, however, lies in the particularities of human language. For example, ironic and sarcastic statements are difficult to detect, which can lead to a wrong interpretation of the statements [62].

2.4 Existing Process and Research Support Tools

Different software solutions with the direct or indirect purpose of making the process of technology management more efficient have been introduced to the market in recent years. Before introducing the approach discussed in this paper, existing market offerings are considered. Since the respective tools have different approaches, they are divided into categories. These categories were defined from 2016 to 2018 at the Invention Center[1] on the RWTH Aachen Campus in joint projects with various industrial companies that wanted to identify software solutions for technology and knowledge management. On the one hand, a distinction was made between whether the solutions focused on information or on data and processes, and, on the other hand, whether the tools provide more general support, or a solution geared to specific use cases, as shown in figure 2.

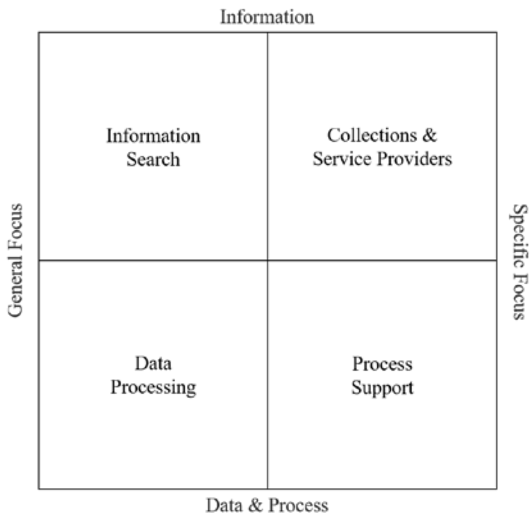

Figure 2: Tool categories derived from the dimensions content orientation (generic vs. specific) and functional focus (information vs. data & process).

Accordingly, there are four categories:

- **Information Search** solutions support the information procurement process by providing easy access to research data, patents, and similar sources.
- **Data Processing** tools allow to solve complex processing and analysis tasks related to text or numerical data.
- **Collections and Service Providers** offer pre-processed data sets, like company directories, or offer specific scouting and research services.
- **Process Support** solutions focus on the technology management process itself and provide organization, visualization, and stage gate tools.

Of course, the categories are not fully selective, and all tools rely on different methods of Artificial Intelligence and Data Analysis. In the following, exemplary tools for each of these categories are presented and their functionality to provide a better understanding of the existing market offerings is described. These tools proved to be typical representatives of the individual categories in the mentioned joint projects and were considered in more detail by the participating companies. To date, these tools and comparable tools have evolved, and new solutions have been added, so this list cannot be considered complete. The sorting is alphabetical without valuation.

[1] https://invention-center.de/

2.4.1 Information Search

Tools for Information Search focus on the integration of multiple data sources into a separate, homogeneous database. In this way, providers can offer their own efficient research tools and evaluations of the research results, and they save the user the time-consuming search in different sources and often the manual preparation of the results as well.

For example, the following solutions can be placed in this category:

Ezassi offers a process support tool for innovation management as well as a solution for technology scouting. The technology scouting database includes research and patent data as well as news and market information. This allows both, technologies, and related companies, to be identified, and possible potentials and obstacles to be identified. Furthermore, Ezassi enables the calculation of a scoring of potential innovations, which supports the assessment process. (https://ezassi.com/)

Mapegy started with a very patent-centered database and has now developed into a complex database that allows searches in news, research data, patents, or trend information as well as in data on companies, start-ups or universities and visualizes the results. (https://www.mapegy.com/)

Mergeflow is comparable to Mapegy, but also focuses on the generation of individual reports based on the respective search. Both providers, Mapegy and Mergeflow, additionally allow access to the data via an programming interface, so that the research results can be used in the user’s own solutions or, for example, in process support tools. (https://www.mergeflow.com/)

2.4.2 Data Processing

Offers for data processing usually do not have their own content focus but provide different building blocks for further processing of data. This can include both the analysis of numerical data, for example the identification of regularities and anomalies, and text analysis, for example the identification of word frequencies, as explained above. The following can be regarded as exemplary tools in this category:

Datameer is a (Big) Data Processing tool that allows to merge different data streams, and to prepare them for evaluation, analysis, and further use. The focus of Datameer is more on numerical evaluations, but in general linguistic analyses, e.g., word frequencies, are also possible. In general, the tool is particularly aimed at data analysts. (https://www.datameer.com/)

RapidMiner allows to assemble the data processing from different components in a kind of construction kit by means of a graphical user interface. The components have data input and output endpoints which are used for initial data input, data transfer between the components, and result output. The contained building blocks cover different analysis activities, which also enable decision making. (https://rapidminer.com/)

Watson is a comprehensive AI solution from IBM. With the help of Watson, a variety of analyses, evaluations, interpretations as well as predictions can be carried out on any data. There are already many interesting Watson use cases, but for a very specific use an appropriate adaptation and training effort must be considered. (https://www.ibm.com/watson/)

2.4.3 Collections and Service Providers

This category summarizes the providers who curate their content or large parts of their contents, or who tailor their offer very specifically to the user's concrete questions. This can be done by editorial selection or follow-up of the information provided, by specific configuration of the offer for the given information needs or also by individual consultation. In return, the offers are often less broadly based in terms of content. The following solutions are examples of such offers:

Findest is an AI-based service. The customer requests a concrete technology scouting, which is translated into a formal query in a kick-off meeting. Based on this query, the underlying AI system determines relevant technology information from various connected data sources. In an intermediate meeting, the customer can refine his query based on the interim results, so that in a final phase the scouting result in form of relevant technology information can be determined and provided. (https://www.findest.eu/)

KEX.net offers subscriptions of information collections on selected topics like Additive Manufacturing. The information is merged from different data sources, classified, and provided in a database as well as different visualizations like technology radars. In addition, the collected information is qualitatively enriched and evaluated by an editorial team. (https://kex.net/)

Trendexplorer focuses on current trend news in different industries. Employees record worldwide news on relevant technologies and innovations, which are then edited and posted on the platform. Users can specifically search for suitable trends within their industry, view similar trends, and compile and share their own collections. (https://www.trendexplorer.com/)

2.4.4 Process Support

Finally, there are offerings that focus very specifically on supporting innovation or technology management processes. Here, the focus is usually less on the provision of information than on the provision of tools for the individual process steps, e.g., for the input, further processing, evaluation and visualization of information and knowledge based on it. Corresponding offers in this category are for example the following:

4strat provides a solution to collect different indicators for strategic forecasting. For this purpose, information from different sources can be combined with own data in a cockpit and be provided to experts. In addition, it is possible to purchase additional content in the form of reports or the commissioning of technology scouting. (https://www.4strat.de/)

Fibres provides a similar service but places additional focus on linking the individual elements with each other. In addition to your own content, further information can be purchased as well, for which Fibres collaborates with various partners. (https://www.fibresonline.com/)

Itonics offers a tool package for technology management that aggregates and classifies individual data sources such as patents and news, from which users can derive and evaluate technology profiles. The results can be visualized in various formats and can be included in a roadmapping tool for planning purposes. (https://www.itonics-innovation.com/)

2.4.5 Further Approaches

The previously mentioned examples are just a brief excerpt of existing solutions. Furthermore, there are continuative or new approaches that may also become relevant in the future or based on which new developments can be initiated.

E.g., **Prisma Analytics** relies on the Quantum Relations approach in Business Intelligence and may be applied in Technology Management in the future as well. The principle of quantum relations (QRP) is an interdisciplinary epistemological approach based on the philosophy of process, the theory of relativity, quantum mechanics, systems theory, and cognitive and social science [63, 64, 65].

In the **syncTech** research project a technology wiki was conceived as a semantic technology database [66, 67]. The wiki is compiled from technology profiles which are linked with each other in a semantic way. Goal of this project was to handle complex and multi-layered technology topics of the lighthouse project Industry 4.0 in an easier way.

Also, the **Heinz-Nixdorf Institute** developed an innovation database as a so-called morphological toolbox to support the tracking of technological diversity and to create an operational development roadmap out of innovative product ideas [68, 69].

In addition to foresight companies that provide analyses supported by AI methods, there are still institutions worldwide whose analyses continue to be primarily **based on expert knowledge** and are supported by long-established methods such as the Delphi method [70]. To name just a few: Institute of the Future based in Palo Alto (California, United States), VDI Tech based in Düsseldorf (Germany), Unity based in Paderborn (Germany) or the Future Institute from Frankfurt (Germany) and Vienna (Austria).

3. Approach of a Data-Driven Technology Management Supported by AI Solutions

The approach follows the concept of a fully structured technology database, which provides a well-founded overview of individual technologies, fields of technology and links between technologies. Such a database is motivated by engineers and researchers who need support on specific questions about technological solutions for technical obstacles or scientific questions [71, 72, 68]. To actively support their everyday work, a high granularity of technological knowledge is required, which cannot easily be provided by technological trend statements [73].

Additionally, this database is prepared and filled with support of artificial intelligence approaches to reduce manual effort which is costly and time-consuming.

This chapter describes the components of this approach, beginning with the structure and database and followed by artificial intelligence approaches. Subsequently, it explains how they work together to support the technology management process.

3.1 TCB and SETS

The foundation of the necessary systematic approach relies on the principle of “Technologie Chancen Bewertung” (TCB), which can be translated as “Technology Opportunities Evaluation” [74, 75, 76]. TCB comprises methodology, database, and user interface with appropriate query options. The methodology enables structured identification of the developments in vast technology landscape and the storage of this information in the Technology Database. In this regard TCB can be viewed as a tool to break down the complexity of the technology landscape.

To use the TCB data for the provision of solutions to overcome obstacles in technical systems or technology projects, an additional system for linking the technology database with that for technical systems and technology projects called “Systematische Entwicklung Technologischer Systeme” (SETS), which can be translated as "Systematic Development of Technical Systems", was introduced [77]. Like TCB, SETS covers the methodology, the database, and the interface with query options, and it can be linked very efficiently to TCB. The difference to TCB is that the structured information is that of technical systems or technical projects to be stored in a technical data base. Both approaches were registered for patent in 2009 by BMW Munich as current assignee [74, 75, 76, 77].

3.1.1 Introduction to the TCB-System

As already described in chapter 2.1, the technological landscape can be characterized by parameters like breadth and depth, interconnectivities, converging technologies, dynamics, and different views on technologies, e.g., by research, society, or economy [12].

The TCB approach is using those parameters, among others, to describe technologies in sub-technology profiles on the necessary granularity level. These profiles contain clusters of attributes such as synopsis, demand, interconnectivities, environmental factors, technology path, and related markets respectively applications. By these sub-technology profiles, the complexity of the technology landscape is broken down into practical pieces which are homogeneously structured. Because of this, they can be easily compared, queried, and managed in a common database.

An example of a sub-technology profile regarding RFID is shown in figure 3. The first categorization level represents a technology area, followed by technology families in level two and finally the third level containing the specific sub-technologies. This third level has the necessary granularity to enrich the content with detailed attributes, e.g., a description or a graphical illustration, and to display the interconnectivity of technologies [74]. This way, TCB enables structured identification of the development in vast technology fields as well as an intelligent storage of this information in a central, homogeneous technology database.

The TCB user interface and its searching capabilities aim on a simple, functional, and navigable design. The interface offers the user an easy way to navigate through the sub-technologies. In addition, a connectivity search enables a more in-depth search and thus access to the specific attributes. These attributes are a set of pre-defined characteristics which, when filled in, provide both a basic description of the sub-technology and its impact on the world or the world in turn on it [75].

If, for example, an engineer wants to enhance the brightness of headlights without changing energy consumption or heat output, TCB would not only be able to list relevant technologies but would also be able to present a view of the entire environment to which these technologies belong. This is the essence of the connectivity search: to semantically determine what type of information is queried, then through interconnectivities and relevant descriptive attributes not only be able to present technological solutions, but also to provide a picture of the world around where the technology, e.g., is economically or environmentally relevant. This refers to TCB as a tool to deal with the complexity of the technology landscape as discussed earlier. Technological functions are a good recognition feature when identifying networks of different technology paths. The results of LINDEMANN's physical effects collection [78] are applied in this context.

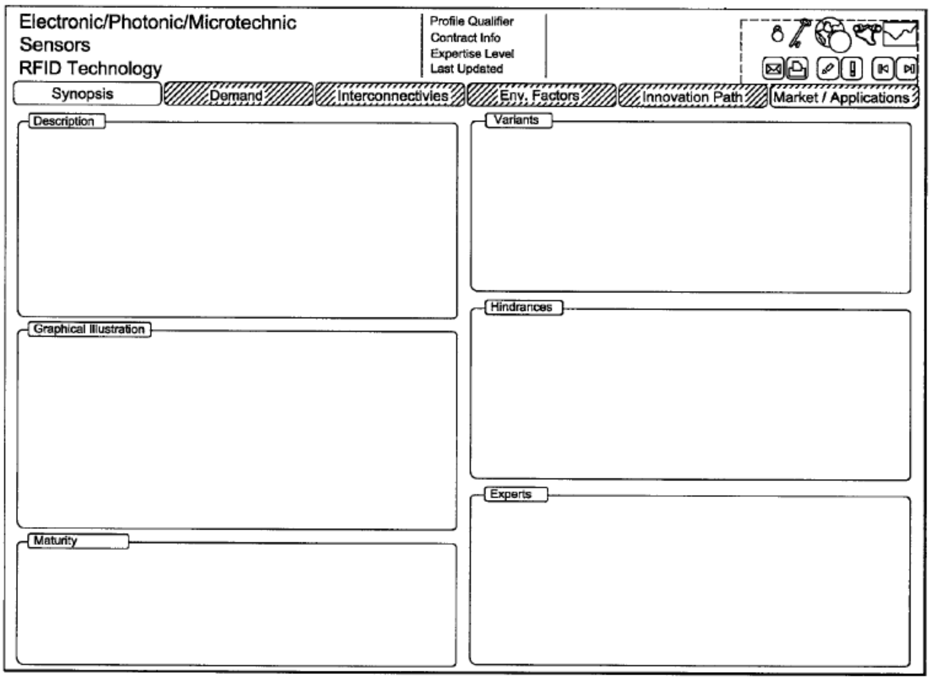

Figure 3: Example sub-technology profile in TCB [74, 78].

However, it is not sufficient to merely make technological solutions discoverable. It is also necessary to relate them to the appropriate projects and project staff. For this reason, another important element of the TCB sub-technology features is the demand for the technology. This demand can link internal information needs with external information as well as provide a quantitative comparison of the general potential of a technology in relation to its internal relevance, whereby the underlying parameters and their weighting must be determined on a company-specific basis.

Thus, it is not only possible to connect sub-technologies with internal projects, but also to judge a technology's relevance. This has two implications: First, when new technologies are identified, their relevance to the company can be assessed immediately. Second, once a technology has been merged with internal projects, innovations that have the potential to modify or replace that technology can be immediately notified to the appropriate project teams. In addition, the information can be quickly checked for its suitability for use.

Since interconnectivity attributes can contain information about the usage of certain sub-technologies in projects or applications, the database can already provide a benefit within an entire company. Nevertheless, the information value can be further increased if additional information about the internal technology usage is also collected, e.g., further details about projects and their teams or used technical systems, which is why the SETS system is introduced in the following.

3.1.2 Introduction to the SETS-System

To keep track of the fast-developing opportunities in the interconnected technology landscape, and to make efficiently use of them, a systematic link must be provided between the technologies and the related technical systems and projects.

With the TCB system, the technology information is well organized in the sense of the offer and shows which technologies are generally available. Now the question arises, how the information in the sense of the need must be structured, to be able to make a simple connection from the need to the existing offer. Since TCB uses technology categories such as areas, families and sub-technologies, SETS offers the approach to categorize the technical system by project level, sub-project level and component level.

The breakdown of such a technical system and the characterization by parameters is shown in figure 4. In the technical layer the technical system is broken down into components and these components are characterized by some attributes such as principles or technological functions as well as problems or technical obstacles and physical effects [78].

If, for example, the project "E-Mobility" is structured in the sense of SETS, this complex topic can be divided into sub-projects such as electric drives, energy storage, energy generation, infrastructure, etc. The next level of subprojects could be the powertrain, power electronics, batteries, heating, and cooling system, etc. for electrically powered cars [77].

Because these attributes are part of TCB as well, the link between both systems can be established by them. In addition to the project information already stored in the TCB sub-technology profiles, this provides the opportunity to search for problem solving ideas on the technical system side and the other way around, see figure 5.

With the additional SETS system, the technology information organized by the TCB can be better used to find solution sets to solve technical problems, especially when the underlying projects consist of many different and diverse technologies. In this case, SETS works like a corporate ontology that gives meaning to information by linking it with each other [79, 80, 81].

The field of vehicle manufacturing is another example where many different ongoing development efforts are taking place in many different technology areas. These efforts are typically undertaken by different development teams that are not necessarily in contact with each other, even if their work overlaps. In addition, there has been no systematic approach to addressing and identifying potential technology-based solutions to the various technological barriers that can arise in such development efforts.

Heating and Cooling BEV

Technical Layer		Technological Layer			
Technical System	*Technical Components*	*Principles/ Technological Functions*	*Problem / Technical Obstacle*	*Physical Effects*	
Cooling circulation system					
	Compressor				
	Electromagnetic coupling	transmit torque		transform electrical into mechanical energy	
	Rotating shafts	increase coolant pressure			
	Condenser with a fan	Phase-change of the coolant		forced	
		dissipate heat		convection	
				improve semiconductors with different thermal radation	
	Fluid tank with a filter drier				
	Pressure sensor	measure the static pressure			
		transmit data to the automatic control		electrical signal transmission	
	Filter drier	reduce humidity (dehumidify)			
	Evaporator expansion valve				
	Pressure control	measure the end evaporator pressure			
		measure the temperature			
		calibrate the evaporator pressure			
	Evaporator with a fan (radiator)				
	Evaporator				
	Temperature sensor	measure the temperature			
		transmit the data			
	Fan	produce the needed air flow			
		rewind the evaporator surface			
	Condensating water tray	collect the cond. water from the evaporator			
		lead the cond. water away			

Figure 4: Breakdown of a technical system into components which are characterized by attributes like technological functions, technical obstacles, and physical effects [77, 78].

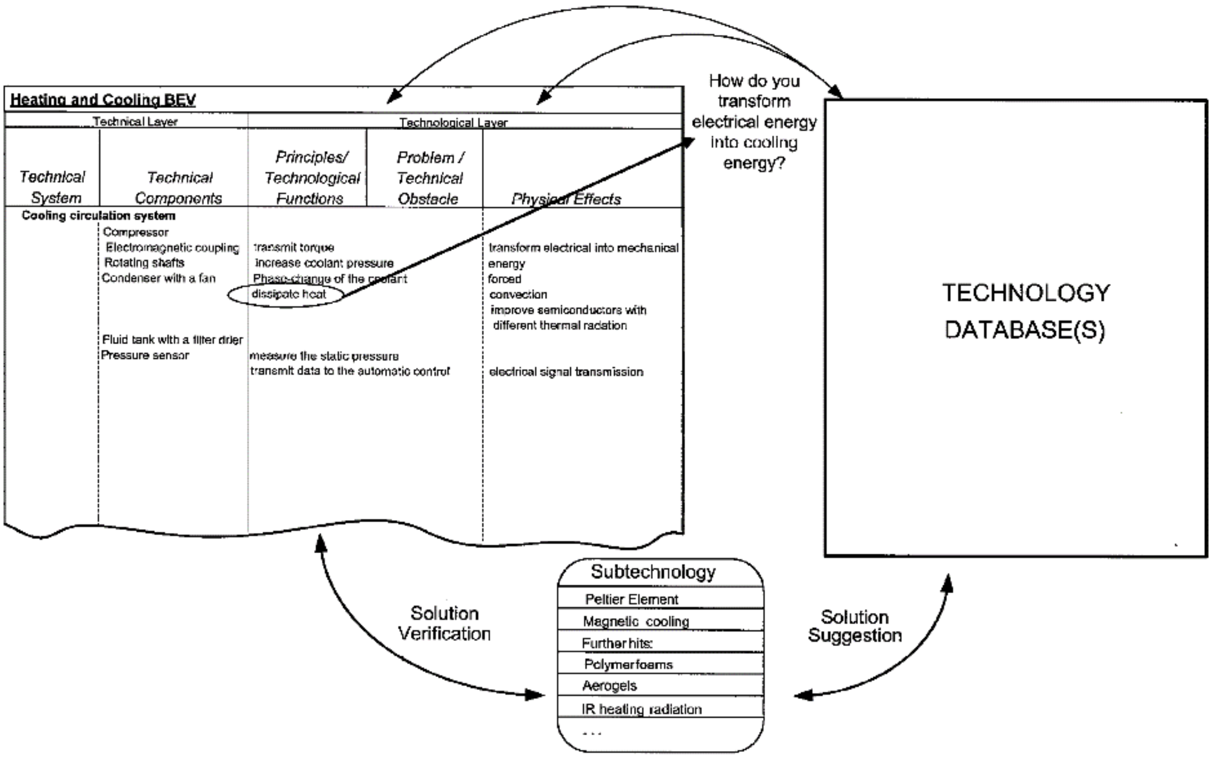

Figure 5: The graphic shows the solution proposals obtained from the technology database and the verification of the solution also for a heating and cooling system [77].

3.1.3 Combination of TCB and SETS

As described in the patent application for SETS [77], the individual systems of TCB and SETS can be interconnected to form a complete system to support project teams working on technical problems of a complex nature in finding solutions.

The TCB system is representing the supply side of solutions from the technology landscape which is broken down to the lowest level of sub-technologies and described by attributes. The SETS system is standing for the demand side looking for solutions for technical problems hidden in the technical project landscape which in SETS is broken down to the level of components and technical functions. The connection between TCB and SETS is established by attributes of the same type, such as technological functions.

In contrast to figure 5, which presents how the TCB and SETS systems work together to find solution impulses for a single problem application, figure 6 shows how this connection works at a full project scale, generating different solution impulses and collecting all the results into what is called a potential solution set.

The upper part of figure 6 represents the project landscape as the current project and previous and parallel projects. The lower part shows the technology landscape with technology databases built from sub-technology profiles to which the technical side is connected by mutual attributes. Both parts are described in more detail before.

In addition, the diagonally striped area shows the potential solution set as a new approach of collecting all solution knowledge generated in the process of using TCB, SETS and other sources such as external databases, development partners, or simply the Internet.

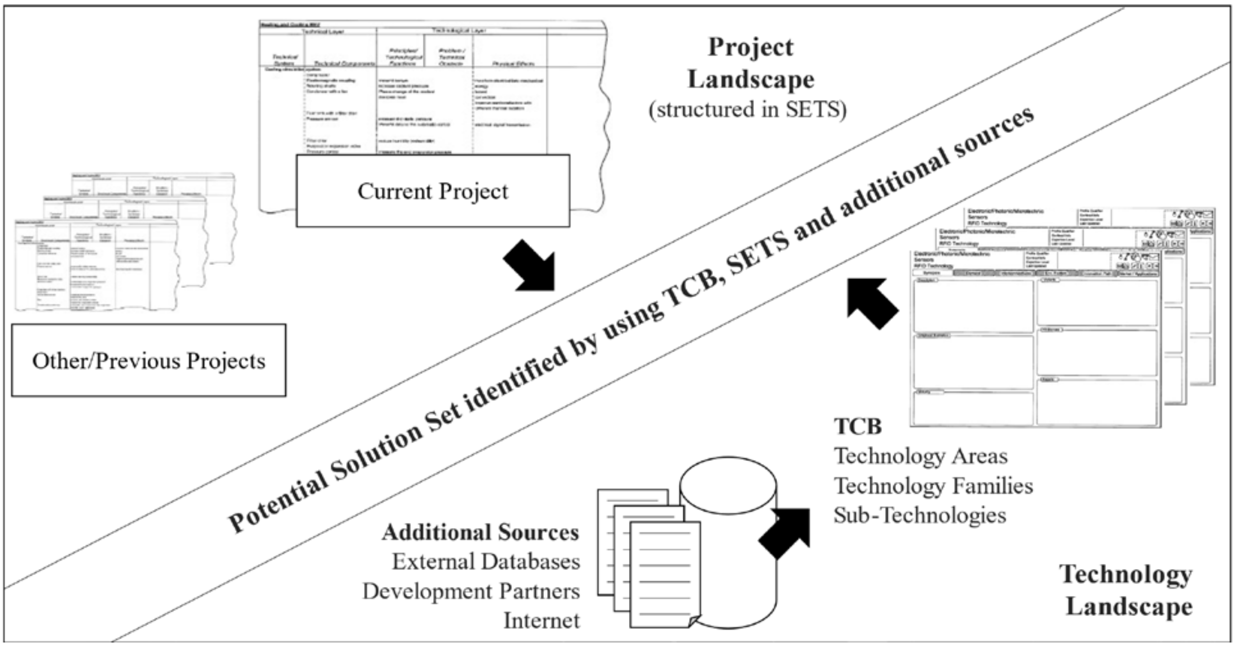

Figure 6: Interconnection of TCB and SETS [77].

After TCB and SETS were developed and tested for their effectiveness as a prototype at BMW Munich in cooperation with the Laboratory for Product Development at the Technical University of Munich ten years ago, more advanced IT solutions such as semantic databases and efficient search algorithms can be used today [82, 83, 84], as well as simpler user interfaces, more effective ways of communicating results, or tools for extracting scenarios or roadmaps [85, 19].

However, the challenge for both systems remains the initial and ongoing filling with enough, complete, and high-quality information at the granularity level of the sub-technologies, which are prepared for the breakdown by attribute structure.

3.2 Research Automation

Before information can be classified and structured, it is initially gathered from various sources. The simplest solution for procurement of enough, complete, and high-quality information to fill a technology database is the purchase of an existing database or the use of interfaces provided by existing solutions. This is meaningful if the available databases already satisfy the existing information need. If, however more specific information is required, whether in the sense of the topical adjustment, or in the sense of the seized information, an own information procurement is necessary.

As already explained, a manual research for relevant information is not target-oriented, so that efficient approaches of automation must be pursued. Regarding Technology Management, information retrieval plays a central role in Technology Intelligence. For permanent use, a technology database should not only be filled once but also be continuously updated and extended. Only in this way can the database be used for regular scanning and scouting activities and support long-term technology monitoring as well.

Accordingly, it is investigated which process steps within the Technology Intelligence activities are suitable for being supported by current Artificial Intelligence approaches and therefore for being at least partially automated to identify relevant documents and extract as much information to evaluate it in terms of TCB/SETS categories, attributes, and connections.

3.2.1 Automation of the Technology Monitoring Process

The process of technology intelligence can always be divided into four steps [17], see figure 7. Based on the technology strategy, the company's specific information needs are defined to align the content-related direction of the further research process. Subsequently, the information search is performed. Beside the actual information research, this also includes the preceding selection of appropriate information sources. The next step comprises the analysis and assessment of all previously collected information. Finally, these analysis' results are prepared to be communicated, e.g., as a management summary for the company's decision-makers.

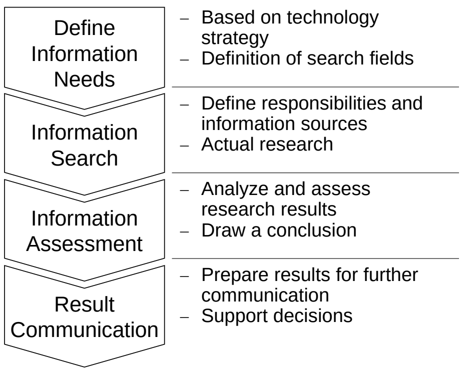

Figure 7: The four process steps of the Technology Intelligence activities scanning, scouting, and monitoring, as well as the processed tasks and its objective per step, based on [17].

Regarding the previously presented possibilities of Artificial Intelligence, the steps of information retrieval and information evaluation are particularly suitable for automation. After the information needs are defined and at least the initial information sources are chosen, a Focused Crawler can parse the available sources and thereby do classification and evaluation [86]. Based on this evaluation, the crawler decides on how to proceed with the parsing process. In addition, it can, compared to a human knowledge worker, permanently continue the work, only restricted by system limitations such as storage.

As an alternative to the Focused Crawler, classic web crawling approaches [47] can also be used, which do not make a content-based decision on how to proceed but track all existing links. In this way, no links are omitted, but at the same time efficiency and the quality of the results are reduced because an undifferentiated data collection is created.

The collected information can then be analyzed and evaluated. Named Entity Recognition can be used to determine which technology or which market participants are involved in a text, and sentiment analysis can be used to determine the mood or position represented in the text. These results can be stored as attributes in TCB and be used to create connections between technologies in TCB and to projects in SETS.

3.2.2 Configuration Model for Focused Crawlers

A native web crawler loops through all websites within a queue of website URLs, also known as frontier, downloads these sites, stores the contents in its database, adds all links stated in the downloaded websites to its queue, and finally proceeds with the next queue items. Such a database can later be used as an index for a comprehensive web search engine.

Compared to such a comprehensive approach, technology intelligence aims to create a selected and compressed set of only relevant information as it is intended by Focused Crawler solutions. To do so, a Focused Crawler must be able to evaluate the relevance of contents and is therefore more complex than native web crawlers. A concept of a Focused Crawler is shown in figure 8. It is based on four processing layers: network, parsing and extraction, representation, and intelligence.

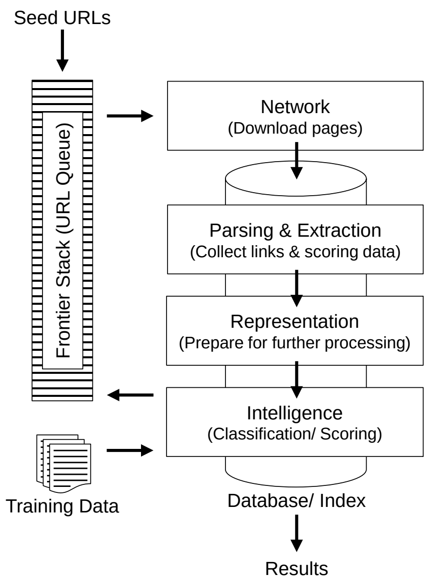

Figure 8: Focused Crawler infrastructure concept according to [51, 86, 87].

Before the crawling process can start, the frontier stack, which contains the list of web pages to be crawled next, must be filled with the first pages to crawl, i.e., with the URLs of manually preselected information sources, the so-called seed pages. Additionally, the crawler needs a set of example documents for the machine learning process to classify the determined information.

Once the crawling process is started, the networking layer will take the next page URL out of the frontier, download the page's content, and store it to a database. Next, the parsing and extraction layer disassembles the content to extract information such as new links which are then used for the further pathfinding and classification.

Afterwards, the extracted data of the usually heterogeneous web pages is converted into a standardized format so that it can be used for the further processing. Next, the intelligence layer will do the classification and calculate the probability that the current document and included URLs are relevant for the current search request. This probability will be used as scoring with which all new URLs are added to the frontier. Now, the process can start over and take the next page URL out of the frontier.

Beside the detailed descriptions in [48, 51], further brief descriptions of Focused Crawler's and their working method are given in [88, 89].

The described Focused Crawling process steps, especially in the intelligence layer, can be implemented in very different ways. This starts with the selection of algorithms and procedures, e.g., whether a simple probabilistic classifier such as a Bayesian Network or Deep Learning for building a complex Artificial Neural Network is used for classification, but also how much training data is provided and with which seed pages the research process is started.

There is no general solution how to implement the crawling process because it must be tailored to the specific application. For example, if a company wants to be a pioneer in its technology area, it is important not to miss any information and to focus the research preferably on scientific publications that deal with new technologies before they are ready for the market. A fast follower, on the other hand, concentrates on solutions that are almost ready for the market, for example based on press releases and patents of competitors.

A higher accuracy and a clear focus in the research process usually require more complex algorithms and more training data, which is associated with an increased initial effort. A search with a low focus is easier to set up and may also accept inaccuracies but leads to a larger result set and thus higher post-processing effort. It is therefore necessary to adapt the implementation of the crawler to your own needs and to approach an optimal solution iteratively.

3.2.3 Filling of TCB and SETS

If first research results are available, these can be assigned to existing database entries in TCB and SETS using the Named Entity Recognition, e.g., as supplementary sources of existing company or technology data, or even new database entries can be created if a company or technology is not yet available. Further investigations via text mining can also be used to identify key figures in the text, which can be used to update database fields directly. E.g., an article could contain concrete information about an improved build-up rate of a specific 3D printing process, which can be identified as a key figure and update the stored technology information.

Once relevant information has been successfully extracted, it can be easily entered into the database, as TCB and SETS already work with clearly defined attributes. On the other hand, TCB and SETS can also provide a blueprint on which information should be focused to reduce the complexity of the automated search and extraction process.

3.3 Alerting

The automated filling and updating of a database are already an advance over a database that is not updated over a longer period and thus loses relevance and value. However, if the new findings are only updated without new knowledge being drawn from them or if the results are not at least randomly checked, the result will only be another extensive data collection, in which again relevant changes are not detected due to the sheer volume.

To counteract this, a targeted alerting is suitable. This way, users are automatically informed, e.g., by sending an e-mail or a push notification, if there are changes in technologies relevant for these users. This relevance can initially be established quite easily if the user is somehow assigned to the technology information, for example by being linked as an expert or user in related profiles or because the user has opened or even edited these profiles. A more complex solution could evaluate the links within the TCB/SETS database in the sense of an ontology and thus also identify possible relevant changes beyond the entries directly touched by the user.

In addition to the actual intention of alerting users to new findings, this also means that changes made by the system are regularly checked by users and corrected if necessary, which leads to a training effect for the system.

4. Discussion

When extracting results from the huge amounts of data available today, two directions can be distinguished in the form of the deductive approach (top-down) and the inductive approach (bottom-up).

The deductive method works on a generic level and investigates trends as well as market and technology developments outside the company. An important intention for companies to follow this approach is to track early signals of change associated with their core business. The results are applied, e.g., within the foresight process and prepared, e.g., in the form of graphics in such a way that they can be used as a basis for strategic decisions which then have an impact on the concrete roadmap and development processes within the company. The research question and results can be stored in a database for further follow-up or as a basis for subsequent research.

In contrast, the inductive method works based on the company's internal technology database, which is structured on a much more granular level of so-called technology profiles. Thus, it is possible to search the existing knowledge database in a very concrete way for technological applications and solutions that provide potential solutions to generic problems.

In the presented TCB system, developments in the technology landscape are represented by such sub-technology profiles, which, structured according to attributes, on the one hand achieve a very fine granularity via technological effects and on the other hand, beyond the variety of attributes, represent developments beyond the purely technological. The sub-technology profiles summarize all information that can be found for the respective attributes. In the future, due to the identical structure of the stored sub-technology profiles, intelligent search algorithms make it possible to quickly draw comparisons, detect correlations, derive trend statements, aggregate them to the superordinate levels, and to find possible solutions for technical obstacles. The search for solution impulses can be further improved with the SETS system, which is also presented, since this database maps a structure based on the same attributes.

The added value of TCB and SETS can unfold company wide. For example, it creates transparency about technological topics such as dynamic developments, networking, opportunities & risks, global competencies, etc., helps to assess the future viability of suppliers and the technological value of innovations, supports the search for new competencies in the human resources area, can focus the work of technology scouts more strongly, and supports more accurate predictions of future resource use in the production area.

Thus, TCB and SETS in combination are particularly suitable for supporting the inductive approach starting from a technology database based on the knowledge available from the outside landscape and within the company. Otherwise, with the deductive approach the search for weak signals starts in the complexity of the outside world instead of the concrete technology landscape within the company. Relevant information must first be identified and then transferred to the existing database. Of course, TCB and SETS can also be used to store the results of deductive research activities and link them to the internal technology knowledge.

However, if the outside world is to be explored manually, this is a costly process that is valuable for the company's orientation but is often avoided. This time and cost expenditure for building and updating the database can be reduced considerably by using suitable AI methods that ensure partially automated search, filling and updating. For this purpose, the use of database interfaces for research within homogeneous data structures and Focused Crawlers for heterogeneous sources were considered. The evaluation and derivation of attributes can be done via text classification or segmentation, named entity recognition and sentiment analysis.

So, it is possible to combine database projects for storing, using, and linking technology knowledge within the company, as comprehensively described by TCB/SETS, with the complexity of the available amount of information, thus combining the deductive and inductive approach. Therefore, such a system would also offer a significant advance over most existing solutions, which usually follow only one deductive or inductive approach each.

5. Conclusion

At the beginning of this paper, it was explained that the technological landscape is growing rapidly and thus becoming more and more complex. A well-structured technology management can help companies to keep up with these dynamic developments. However, to do so, it is necessary to manage the enormously growing amount of important data in the field of technological innovation to identify relevant developments at an early stage and to derive the need for action on this basis. Well-structured technology databases such as the combined TCB/SETS system can help in this process.

Moreover, with the abundance of information and the rapid up-to-dateness, it is becoming increasingly difficult to keep up with purely manual means. This is where AI approaches can provide support, which can quickly derive current and relevant insights for the company from the huge amounts of data from the various development paths of technologies, to ensure that the database is complete and up-to-date and thus gain a competitive advantage.

This combined inductive and deductive approach allows a comprehensive view, but currently still finds its limits in the performance of the AI methods. For this reason, the following open research questions and related activities are considered.

6. Outlook

Even though AI methods already offer noticeable support for the filling and maintenance of databases, there is still a long way to go before processes are largely automated. To make this possible, further challenges must be solved, especially in Natural Language Processing.

The first question that arises is how new technologies and technological developments can be identified and named to automatically expand and complete the technology landscape [90].

Furthermore, it must also be determined which attributes are necessary to comprehensively describe a sub-technology and identify important connections. Accordingly, it is also necessary to check these attributes for completeness within the database and to specifically detect missing information. From a technical point of view, it must be examined which database systems and data models are suitable for storing and evaluating the attributes and interconnections. Instead of relational databases, for example, document- and graph-based databases could be useful, especially to map semantic information. Algorithms for identifying information in heterogeneous sources need to be further researched and improved to fill attributes in a targeted manner not only by efficient path finding and precise classification, but also by targeted extraction of the right information, not only in the form of concrete values, but also by interpretation of linguistic paraphrases. An example of this is an automatic determination of the Technology Readiness Level, in short TRL [91], as is being aimed at in the TechRad research project [92, 93].

In addition, it is important to further develop the interface and internal database search algorithms to enable ergonomic and efficient access to the available information so that the database does not at some point confront the user with the problem of information overload as well. This also includes meaningful visualizations of the information and the transfer into decision templates and planning tools such as technology roadmaps.

Finally, the general development of AI technologies can be observed. If the systems will be able to reliably recognize semantic relationships and draw cognitive conclusions, performance will increase significantly, and new possibilities will arise [94].

Acknowledgements

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References

[1] Spath, D., Linder, C., Seidenstricker, S., 2011. Technologiemanagement. Grundlagen, Konzepte, Methoden. Fraunhofer Verlag, Stuttgart.

[2] Stankosky, M., 2007. "Editorial". VINE 37 (4), https://doi.org/10.1108/vine.2007.28737daa.001

[3] Hachmöller, A., Knoche, M., Schuh, G., 2006. Technologiemanagement (ab 1986), in: Eversheim, W., Pfeifer, T., Weck, M. (Eds.), 100 Jahre Produktionstechnik. Werkzeugmaschinenlabor WZL der RWTH Aachen von 1906 bis 2006. Springer, Berlin, pp. 693-703.

[4] Kurzweil, R., 2001. The Law of Accelerating Returns. https://www.kurzweilai.net/the-law-of-accelerating-returns (last visited 2020-10-09).

[5] Van den Bosch, A., Bogers, T., De Kunder, M., 2015. Estimating search engine index size variability. A 9 year longitudinal study. Scientometrics 107, pp. 839–856, https://doi.org/10.1007/s11192-016-1863-z

[6] Hilbert, M., Lopez, P., 2011. The World`s Technological Capacity to Store, Communicate, and Compute Information. Science 332 (60).

[7] Jinha, A. E., 2010. Article 50 million: an estimate of the number of scholarly articles in existence. Learned Publishing 23 (3), pp. 258-263.

[8] Ware, M., Mabe, M., 2015. STM-Report, An overview of scientific and scholarly journal publishing. Celebrating the 350th anniversary of journal publishing. 4 ed. March 2015.

[9] U.S. Patent Statistics Chart Calendar Years 1963 – 2019, U.S. Patent and Trademark Office Patent Technology Monitoring Team (PTMT), updated 4/2020, https://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm (last visited 2020-09-14)

[10] Reger, G., 2006. Technologie-Früherkennung: Organisation und Prozess, in: Gassmann, O., Kobe, C. (Eds.), Management von Innovation und Risiko. Quantensprünge in der Entwicklung erfolgreich managen. Springer, Berlin, pp. 303–329.

[11] Bullinger, H.-J., Schäfer, M., 1997. Entwicklungstrends und Herausforderungen im Informationszeitalter, in Bullinger, H.-J., Broßmann, M. (Eds.), Business Television. Beginn einer neuen Informationskultur in den Unternehmen. Schaeffer-Poeschel, Stuttgart, pp. 3-15.

[12] Bullinger, H-J. (Ed.), 2009. Technology Guide – Principles, Applications, Trends. Springer, Berlin, Heidelberg, New York.

[13] Schuh, G., 2014. Der Ordnungsrahmen Produktion und Management, in: Schuh, G. (Ed.): Einkaufsmanagement. Handbuch Produktion und Management 7, 2 ed. Springer Vieweg, Berlin, pp. 1–4.

[14] Klappert, S., Schuh, G., Aghassi, S., 2011. Einleitung und Abgrenzung, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 5-10.

[15] Rüegg-Stürm, J., 2004. The new St. Gallen management model: Basic categories of an approach to integrated management. Springer, Berlin.

[16] Schuh, G., Klappert, S., Moll, T., 2011. Ordnungsrahmen Technologiemanagement, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 11-31.

[17] Wellensiek, M., Schuh, G., Hacker, P. A., Saxler, J., 2011. Technologiefrüherkennung, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 89-169.

[18] Schuh, G., Klappert, S., Orilski, S., 2011. Technologieplanung, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 171-222.

[19] Möhrle, M. G., Isenmann, R., 2017. Technologie-Roadmapping. Zukunftsstrategien für Technologieunternehmen, 4 ed. Grundlagen des Technologie-Roadmapping, Springer, Berlin, Heidelberg.

[20] Klappert, S., Schuh, G., Möller, H., Nollau, S., 2011. Technologieentwicklung, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 223-239.

[21] Schuh, G., Drescher, T., Berckermann, S., Schmelter, K., 2011. Technologieverwertung, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 241-282.

[22] Haag, C., Schuh, G., Kreysa, J., Schmelter, K., 2011. Technologiebewertung, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 309-366.

[23] Neemann, C. W., Schuh, G., 2011. Technologieschutz, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 283-307.

[24] Schulte-Gehrmann, A.-L., Klappert, S., Schuh, G., Hoppe, M., 2011. Technologiestrategie, in: Schuh, G., Klappert, S. (Eds.), Technologiemanagement, Springer, Berlin, pp. 55-88.

[25] Ewald, A., 1989. Organisation des strategischen Technologie-Managements. Schmidt, Berlin.

[26] Bullinger, H.-J., 1994. Einführung in das Technologiemanagement: Modelle, Methoden, Praxisbeispiele. Teubner, Stuttgart.

[27] Sauber, T., 2004. Design and implementation of a concept of structured innovation strategy formulation. Dissertation, Swiss Federal Institute of Technology Zurich, Zürich.

[28] Schuh, G., Klappert, S., Saxler, J., 2008. Designing technology intelligence networks in the context of open innovation. In: International Association for Management of Technology. EU-ROMOT 2008.

[29] Wolfrum, B., 2000. Strategisches Technologiemanagement, 2 ed. Gabler, Wiesbaden.

[30] Lichtenthaler, E., 2002. Organisation der Technology Intelligence: Eine empirische Untersuchung der Technologiefrühaufklärung in technologieintensiven Großuntemehmen. Technology, Innovation and management. Industrielle Organisation, Zürich.

[31] Ashton, W., Klavans, R., 1997. An introduction to technical intelligence in business, in: Ashton, W., Klavans, R. (Eds.), Keeping Abreast of Science and Technology. Technical Intelligence for Business, Battelle Press, Columbus, pp. 5–22.

[32] Ashton, W. B., Stacey, G. S., 1995. Technical intelligence in business: understanding technology threats and opportunities. International Technology Management 10 (1), pp. 79-104.

[33] Aaker, D., 1983. Organizing a strategic information scanning system. California Management Review 25 (2), pp. 76–83.

[34] Zweck, A., 2005. Technologiemanagement – Technologiefrüherkennung und Technikbewertung, in: Schäppi, B., Andreasen, M., Kirchgeorg, M., Radermacher, F.J. (Eds.), Handbuch Produktentwicklung. Hanser, München, pp. 169–193.

[35] Bürgel, H., Reger, G., Ackel-Zakour, R., 2005. Technologie-Früherkennung in multinationalen Unternehmen: Ergebnisse einer empirischen Untersuchung, in: Möhrle, M.G., Isenmann, R., Müller-Merbach, H. (Eds.), Technologie-Roadmapping. Zukunftsstrategien für Technologieunternehmen, 2 ed., Springer, Berlin, pp. 27–53.

[36] Krystek, U., Müller-Stewens, G., 1993. Frühaufklärung für Unternehmen. Identifikation und Handhabung zukünftiger Chancen und Bedrohungen. Schäffer-Poeschel, Stuttgart.

[37] Steinmüller, K., 2005. Methoden der Zukunftsforschung — Langfristorientierung als Ausgangspunkt für das Technologie-Roadmapping, in: Technologie-Roadmapping, Springer, Berlin, Heidelberg.

[38] Brodbeck, H., 1999. Strategische Entscheidungen im Technologie-Management. Relevanz und Ausgestaltung in der unternehmerischen Praxis. Industrielle Organisation, Zürich.

[39] Gerpott, T.J., 2005. Strategisches Technologie- und Innovationsmanagement. 2 ed. Schäffer-Poeschel, Stuttgart.

[40] Spaniol, M. J., Rowland, N. J., 2019. Defining scenario, in: Futures Foresight Sci, 1:e3. https://doi.org/10.1002/ffo2.3

[41] Pearson, R. J., Costley, A. E., Phaal, R., Nuttall, W. J., 2020. Technology Roadmapping for mission-led agile hardware development: a case study of a commercial fusion energy start-up, in: Technological Forecasting and Social Change 158.

[42] Durst, C., Durst, M., 2017. Softwaregestütztes Technologie-Roadmapping, in: Möhrle, M.G., Isenmann, R., Technologie-Roadmapping – Zukunftsstrategien für Technologieunternehmen. 4 ed. Springer, Berlin, Heidelberg.

[43] Taddy, M., 2019. The Technological Elements of Artificial Intelligence, in: Agrawal, A., Gans, J., Goldfarb, A., The Economics of Artificial Intelligence: An Agenda. University of Chicago Press, Chicago.

[44] Pouyanfar, S., Sadiq, S., Yilin, Y., Haiman, T., Yudong, T., Presa Reyes, M., 2018. A Survey on Deep Learning: Algorithms, Techniques, and Application, in: ACM Computing Surveys 51 (5). https://doi.org/10.1145/3234150

[45] Ginsparg, P., 2011. ArXiv at 20. Nature 476, pp. 145–147. https://doi.org/10.1038/476145a

[46] US LoC, 2015: Annual Report of the Librarian of Congress for the fiscal year ending September 30, 2014.

[47] Shrivastava, V., 2018. A methodical study of web crawler, in: Journal of Engineering Research and Application, 8 (11).

[48] Chakrabarti, S., van den Berg, M., Dom, B., 1999. Focused crawling: a new approach to topic-specific Web resource discovery, in: Computer Networks 31, pp. 1623-1640.

[49] De Bra, P. M. E.; Post, R. D. J., 1994. Searching for arbitrary information in the WWW: The fish-search for mosaic.

[50] Hersovici, M., Jacovi, M., Maarek, Y. S., Pelleg, D., Shtalhaim, M., Ur, S., 1998. The shark-search algorithm. An application: tailored Web site mapping, in: Computer Networks and ISDN Systems, 30 (1), pp. 317-326.

[51] Pant, G., Srinivasan, P., 2005. Link contexts in classifier-guided topical crawlers, in: IEEE Transactions on knowledge and data engineering, 18 (1), pp. 107-122.

[52] Schneider, K. M., 2004. On word frequency information and negative evidence in Naive Bayes text classification, in: International Conference on Natural Language Processing, Springer, Berlin, Heidelberg, pp. 474-485.

[53] Rennie, J. D., Rifkin, R., 2001. Improving multiclass text classification with the support vector machine.

[54] Arusada, M. D. N., Putri, N. A. S., Alamsyah, A., 2017. Training data optimization strategy for multiclass text classification, in: 5th International Conference on Information and Communication Technology, IEEE, pp. 1-5.

[55] Schmidt, S., Schnitzer, S., Rensing, C., 2016. Text classification based filters for a domain-specific search engine, in: Computers in Industry, 78, pp. 70-79.

[56] Jain, A. K., Dubes, R. C., 1988. Algorithms for Clustering Data. Prentice-Hall, New Jersey, p. 96.

[57] Nadeau, D., Sekine, S., 2007. A survey of named entity recognition and classification. Lingvisticae Investigationes, 30 (1), pp. 3-26.

[58] Anderka, M., Stein, B., Lipka, N., 2011. Detection of text quality flaws as a one-class classification problem, in: Proceedings of the 20th ACM international conference on Information and knowledge management, pp. 2313-2316.

[59] Jung, Y., Park, H., Myaeng, S. H., 2006. A hybrid mood classification approach for blog text, in: Pacific Rim International Conference on Artificial Intelligence, Springer, Berlin, Heidelberg, pp. 1099-1103.

[60] Yadollahi, A., Shahraki, A. G., Zaiane, O. R., 2017. Current state of text sentiment analysis from opinion to emotion mining, in: ACM Computing Surveys (CSUR), 50 (2), pp. 1-33.

[61] Liu, B., 2012. Sentiment analysis and opinion mining, in: Synthesis lectures on human language technologies, 5 (1), pp. 1-167.

[62] Weitzel, L., Freire, R. A., Quaresma, P., Gonçalves, T., Prati, R., 2015. How does irony affect sentiment analysis tools? In: Portuguese Conference on Artificial Intelligence, Springer, Cham, pp. 803-808.

[63] Brauer, G., 2019. Die Bit-Revolution. Künstliche Intelligenz steuert uns alle in Wirtschaft, Politik und Gesellschaft. UVK, Konstanz, München.

[64] Schloer, H., Gagner, P., 2006. Quantum relations theory. A brief overview, in: Spariosu, M. (Ed.) Remapping knowledge. Intercultural studies for a global age, Berghahn, New York, Oxford, pp. 179-195.

[65] Schloer, H., Spariosu, M., 2017. The quantum relations principle. Managing our future in the age of intelligent machines. V&R, Göttingen.

[66] Schimpf, S., Heubach, D., 2013. The wisdom of technology experts: a collaborative and IT-supported approach to monitoring technological developments. Proceedings of the R&D Management Conference 2013.

[67] Korell, M., Schimpf, S., 2015: Das syncTech Modell zur synchronisierten Technologieadaption, in: Warschat, J., Schimpf, S., Korell, M. (Eds), Technologien frühzeitig erkennen, Nutzenpotenziale systematisch bewerten. Methoden, Organisation, semantische Werkzeuge zur Informationsgewinnung, Fraunhofer, München, pp. 8-12.

[68] Gausemeier, J., Brink, V., Ihmels, S., Kokoschka, M., Reymann, F., 2009: Strategic product-and technology-planning with the innovation-database: A field-proven approach from the market-oriented product idea up to an operational development roadmap, in: 2009 IEEE International Conference on Industrial Technology, pp. 1-6.

[69] Ihmels, S., 2006: Technologie-Datenbank Heinz-Nixdorf-Institut – Überblick – Konzeption und Umsetzung, in: Symposium für Vorausschau und Technologieplanung, Heinz-Nixdorf-Institut, Berlin, pp. 139–156.

[70] Linstone, H. A., Turoff, M. (Eds.), 1975. The delphi method, Addison-Wesley, Reading, pp. 3-12.

[71] Zweck, A. (2003): Integriertes Technologie- und Innovationsmanagement. Zur Gestaltung technischen Wandels. Früherkennung, Analyse, Bewertung und Implementierung als Elemente des Innovationsprozesses.

[72] Brink, V., Ihmels, S., 2007. Strategische Produkt- und Technologieplanung mit der Innovations-Datenbank. Fachbericht Produktentwicklung Konstruktion, 11/12-2007.

[73] Institute for the Future, 2005. Ten-Year Forecast Perspectives. https://www.iftf.org/uploads/media/SR-891_2005_TYF_Perspectives.pdf (last visited 2020-10-09)

[74] Boßmeyer, H.-J., Prick, G., Ertl, M., Rath, M., 2009. System and method for utilizing technology interconnectivities. United States Patent Application Publication, US20090271392 A1, European Patent Application, EP2 113 869 A1.

[75] Boßmeyer, H.-J., Prick, G., Ertl, M., Rath, M., 2009. System and method for utilizing organization-level technology demand information. United States Patent Application Publication, US2009271393, European Patent Application, EP2113871 A1.

[76] Boßmeyer, H.-J., Prick, G., Ertl, M., Rath, M., 2009. System and method for providing and managing technology-based information. United States Patent Application Publication, US2009271431.

[77] Boßmeyer, H.-J., Ratz, P., Reger, M., Huber, C., 2009. Method for systematically identifying technology – based solutions. United States Patent Application Publication, US2009271701, European Patent Application, EP2113870 A1.

[78] Lindemann, U., 2006. Checkliste Physikalische Effektesammlung. Lehrstuhl für Produktentwicklung, Umdruck zur Vorlesung Produktentwicklung und Konstruktion, Technische Universität, München.

[79] Bullinger, A., 2008. Innovation and Ontologies. Structuring the Early Stages of Innovation Management, Springer Gabler, Wiesbaden.

[80] Gilchrist, A., 2003. Thesauri, Taxonomies and Ontologies – an Etymological Note. Journal of Documentation.

[81] Berners-Lee, T., Hendler, J., Lassila, O., 2001. The Semantic Web. Scientific American, 284 (5), pp. 34-43.

[82] Simsion, G., 2007. Data Modeling. Theory and practice. Technics Publications, 2007.

[83] Sedgewick, R., Wayne, K., 2014. Algorithmen: Algorithmen und Datenstrukturen. Pearson, München.

[84] Kemper, A., Eickler, A., 2015. Datenbank Systeme. Eine Einführung, De Gruyter, Oldenbourg.

[85] Möhrle, M. G., 2002. TRIZ-basiertes Technologie-Roadmapping, in: Möhrle, M. (Ed.), Technologie-Roadmapping – Zukunftsstrategien für Technologieunternehmen. Springer, Berlin.

[86] Schuh, G., Bräkling, A., Drescher, T., 2015: Configuration model for focused crawlers in technology intelligence, in: Proceedings of 24th International Association for Management of Technology (IAMOT), pp. 832-839.

[87] Schuh, G., Bräkling, A., Apfel, K., 2014. Identification of requirements for focused crawlers in technology intelligence, in: Proceedings of PICMET'14 Conference: Portland International Center for Management of Engineering and Technology; Infrastructure and Service Integration, IEEE, pp. 2918-2923.

[88] Shah, V., Patni, R., Patani, V., Shah, R., 2014. Understanding Focused Crawler, in: International Journal of Computer Science and Information Technologies 5 (5), pp. 6849-6852.

[89] Hernandez, J., Marin-Castro, H. M., Morales-Sandoval, M., 2020. A semantic focused web crawler based on a knowledge representation schema, in: Applied Sciences 10 (11). https://doi.org/10.3390/app10113837

[90] Mühlroth, Ch., Grottke, M., 2020. Artificial Intelligence in Innovation: How to Spot Emerging Trends and Technologies, in: IEEE Transactions on Engineering Management.

[91] Faidi, S., Olechowski, A., 2020. Identifying Gaps in Automating the Assessment of Technology Readiness Levels, in: Proceedings of the Design Society: DESIGN Conference, 1, pp. 551-558. https://doi.org/10.1017/dsd.2020.160

[92] Stroh, M.-F., Benning, J., Emonds, G., 2020. Trends finden und überblicken für KMU, Teil 1, in: MaschinenMarkt 16/2020, Vogel. https://www.maschinenmarkt.vogel.de/trends-finden-und-ueberblicken-fuer-kmu-teil-1-a-956595/ (last visited 2020-10-09).

[93] Arnu, D., Shibata, M.-L., Bräkling, A., 2020: Trends finden und überblicken für KMU, Teil 2, in: MaschinenMarkt 17/2020, Vogel. https://www.maschinenmarkt.vogel.de/trends-finden-und-ueberblicken-fuer-kmu-teil-2-a-962127/ (last visited 2020-10-09).

[94] Pearl, J., Mackenzie, D., 2018. The Book of Why: the new science into cause and effect. Basic Books, New York.

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