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Knowledge bases as a source of innovation

Doctoral dissertation

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Author’s Declaration

No portion of the work referred to in this dissertation has been submitted in support of an application for another degree or qualification of this or other university or other institution of learning.

Furthermore, this dissertation contains no material previously written and /or published by another person, except where an appropriate acknowledgment is made in the form of bibliographical references.

Abstract

Abstract of the dissertation submitted by:
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Decisions are different, some of them do not need support due to their low complexity, they can be made routinely, while others require systematic thinking and support. This dissertation examines the second group and it suggests an approach, a methodology and a tool for consideration. The focus of the research in this study is on the experienced decision maker or the expert who has the knowledge needed to make the decision, but he or she can achieve better results by properly systematizing the prior knowledge and transforming the tacit knowledge elements to explicit. Thus, the thesis is not about data or their analysis but primarily about understanding human behavior and thinking. On the problem level of the dissertation we discuss two questions: how to create new knowledge from this prior experience with the help of Knowledge-bases? How can these decisions catalyze new, innovative ideas? The research highlights that nowadays there is a lot of talk about smart decisions and the tools and processes which support them, but the terms and concepts are not clear. Our proposition is that with the help of a Knowledge Engineer who knows the process of Knowledge Acquisition and the key to the success and difficulties of it, as well as a Knowledge-Based Expert System, a more transparent and acceptable decision result can be achieved. As a finding we demonstrate in this dissertation that smart decisions are not smart because they are made based on as many data as possible, and not because a smart tool makes the decision instead of the human thinker but because the logical thinking path of an experienced decision maker is helped by the appropriate method and tool.

This thesis comprises discussion about cases in which we do not use Big Data or even operation control, but it is also not needed, since the knowledge of the experienced decision maker is available and can be activated in decision making. We present a set of four papers about this investigation with a transdisciplinary approach and its results.

First, we aimed to give a comprehensive picture of the tool, its future within the artificial intelligence domain and its usability and limitations. We tried to find the answer for the research

question of what is the key to better usability, or what is the tool that most supports the process we describe.

After this we followed our research journey with a conceptualization of a collaborative knowledge platform which can create new knowledge and can become the source of innovation by a unique reasoning method. According to our assumption, this could be a form of superintelligence presented.

Finally, we demonstrate practical examples for the two kinds of reasoning, one for the Rule-based Reasoning with a complex dilemma of a CEO of a high-tech SME about where to place a new business unit. At this point of our study, we formulated the following conclusion: the opposition of rational behaving and misbehaving can be dissolved in logic-based behaving as the decision maker confirmed to us that the presented thinking process was useful in problem solving.

The other kind of reasoning, Case-based Reasoning was modeled through a project evaluation process in a University R&D laboratory and our resulting model and the discovered rules showed the three most relevant attributes of the success of the projects. As an extra finding of our journey in these cases, we recognized that the original process, when the process starts with the research phase which is followed by the development, is reversed and actually, these are D&R processes driven by the research curiosity of project managers.

We believe that the results of our research contribute both to the literature of the areas concerned and to knowledge that can be implemented in practice.

Acknowledgements

More than a decade ago, during a previous postgraduate course, I was committed to lifelong learning. Then I started to deal with the form of decision support presented in the dissertation, its applicability, the possibilities of further development and how all this could advocate innovation. We can say that the scientific interest was established at that time, which finally matured in this study. After a few years of gaining practical experience in this field, in 2016 I felt that I needed to continue my research on a scientific level. I wished to find a doctoral program where I could hear new ideas from prominent lecturers of different disciplines that could inspire me and give new perspectives in my research. I found this in the SZEEDS Doctoral Program, where several lectures, international conferences, interesting and valuable new relationships brought me the results that are embodied in this dissertation.

I would like to express my special thanks to my supervisor prof. Zoltán Baracskai, who gave me an opportunity to accomplish these results. With decades of unique knowledge behind him, he supported me by constructive advice, his guidance oriented and inspired me throughout my researching route.

I am grateful to the PADME foundation for allowing me to focus on my research in the last few years and gain new relationships and a wide range of knowledge by publishing and participating in international conferences.

Finally, I am grateful to my family and friends for their patience, encouragement, and support in helping me continue my studies and progress toward my goal over the year.

Table of contents

List of Tables

List of Figures

Key to abbreviations

AI: Artificial Intelligence

CBR: Case Based Reasoning

CKP: Collaborative Knowledge Platform

D&R: Development and research

DSS: Decision Support System

ES: Expert System

KA: Knowledge Acquisition

KBS: Knowledge Based System

KE: Knowledge Engineering

KR: Knowledge Representation

RBR: Rule Based Reasoning

R&D: Research and Development

SME: Small and medium-sized enterprise

1. Introduction

1.1. Knowledge background

Decisions surround us in all fields of life, but most of them do not need support, as we have met them many times, so they are routine decisions. The ones which require any kind of supports are mostly complex dilemmas. In this dissertation, we address complex business dilemmas in which the problem can be solved by gathering and engineering the available knowledge. These dilemmas usually arise during the existence of an organization when its operation reaches a special point which, for some reason, requires systematization of the experience gained so far. The reason can be almost anything. It can be forced by external circumstances, for instance significant changes of the market conditions, or even from internal motivation, such as a new business strategy, but the main point is that it requires consistent consideration. In the last few decades, extensive scientific literature was published on data-based decision support, we can talk about a big data-boom phenomenon, but these studies debate obviously much less about those cases when the appropriate "big data" are not available or not in sufficient quantities or qualities to make a decision. Yet, there are many cases like this, for example, SMEs or educational institutions, where it is still not typical to implement a sophisticated management information system which can provide data in order to support the work of decision makers in a strategic situation. The level of using an integrated information management system at a company, which can be a source of data within a decision-making process, in many cases depends on how big the organization is. Smaller ones often operate without well-organized business information, most of them use special applications only for accounting, finances or sales force. From medium-sized companies upwards, an integrated solution is usually installed with a core system and several add-on applications around, finally a Big Data software analyses a large amount of information from this system for insights, which theoretically leads to better decisions and business actions. These Big Data solutions were added to the systems more or less in the last two decades, nevertheless the act of gathering and storing information for eventual processing matured for a much longer period. These IT tools usually perform very demonstrative data visualization from the collected data of the integrated management system but the usefulness of these charts during a complex business decision is ambivalent. In several cases, end-users admitted that the main reason why they apply the result of the charts from the Big Data tool is that it can be evidence later if things occasionally go wrong – they can claim that numbers and trends indicated their decisions. By now this problem has also been published in one of the most prominent business journals, the Harvard Business

Review. “The conventional tools we all learned in business schools are terrific when you’re working on a stable environment, with a business model you understand and access to sound information. They’re far less useful when you’re on unfamiliar terrain – if you’re in a fast-changing industry, launching a new kind of product, or shifting to a new business model. That’s because conventional tools assume that decision makers have access to remarkably complete and reliable information. Yet every business leader we have worked with over the past 20 years acknowledges that more and more decisions involve judgments that must be made with incomplete and uncertain information.” (Courtney et al., 2013), (Rosenzweig, 2013). It may seem extraordinary that Big Data solutions are mentioned among the conventional tools but those do not ensure that all expectations are provided during the decision-making process. The other issue is that they cannot reliably quantify how many times one of the data is more important than another one and that is the reason for the contraindication of the tools based on scoring and data-weighting used by banks and financial organizations for risk analyses as another type of decision support systems. Concerning the Big Data hype in the last decade, decision makers should take James G. March’s hint (March, 2005) about the irrelevancy of data, saying that decision makers collect a large amount of data, which play a tiny role or even do not play any kind of role in their decisions. It seems March’s model is still valid as Tanya Menon and Leigh Thompson published in their article (Menon & Thompson, 2016) titled “How to make better decision with less data”. They found that “despite all of the data available, people often struggle to convert it into effective solutions to problems. Instead, they fall prey to what Jim March and his co-authors describe as “garbage can” decision making: a process whereby actors, problems, and possible solutions swirl about in a metaphorical garbage can and people end up agreeing on whatever solution rises to the top. The problem isn’t *lack* of data inside the garbage can; the vast amount of data means managers struggle to prioritize what’s important. In the end, they end up applying arbitrary data toward new problems, reaching a subpar solution. To curb garbage-can decision making, managers and their teams should think more carefully about the information they need to solve a problem and think more strategically about how to apply it to their decision making and actions.” In almost every organization, we can find individuals, or we can call them experts, who own usable knowledge elements, even if only in a special topic, that can be acquired with the suitable method in order to apply them in a knowledge engineering process. But why would they share their knowledge with their organization? The earlier theories, which said people work exclusively for financial reward or do anything for their workplace, have long since been overturned. In the age of Motivation 3.0 (Pink, 2009) many people are definitely looking for professional challenge opportunities and those where their expertise, even without financial reward, is recognized. When we examine Rokeach's terminal and instrumental values (Rokeach, 1973), we find several values that cannot come from merely the pursuit of meeting basic needs, and in this new system of motivation, for instance inner harmony, desire for higher intellect, or responsibility can be interpreted differently than earlier. If we accept that these values are important for individuals, we have to accept the motivation in connection with this. This different thinking about values and work within organizations has also emerged among management thinkers, which is largely in conforming to the findings of social psychologists. For example, a knowledge worker, originally introduced by Peter Drucker (Drucker 1959) in the era of high-tech companies places the emphasis elsewhere than an agricultural workingman 80 or 100 years ago or a physical worker next to the assembly line. In addition, a new relevant definition was published for the cultivated minds of practitioners (Velencei, Baracskai, Dörfler & Stierand 2016), who are the educated but semi-specialized human resources of the company and one of their main motivations is learning at both individual and organizational levels. One of these people's professional drivers can be solving complex problems and being a part of a really important and useful thing. It is true for a development or a decision-making process. They own the intellectual capital of corporations and this knowledge can be applicable with benefits in decision situations. In order to motivate people in these processes where problem solving happens, it is essential to enable them to share their stories, viewpoints and expectations. In many cases, it is more important for them than getting a slightly higher salary in another job or grabbing other status symbols in connection with their positions. According to March, who is best known for his research on organizational decision making and organizational learning, people can remember and recall colorful stories and information more easily than data of statistics (March, 1991), so we have to convince them to share their experiences and their stories in order utilize them in decision making. From social perspective, there are symbols behind everybody and these symbols come from their cultural and social backgrounds with certain narratives as starting points of people's expectations. Probably, the importance of story-telling and social narratives in business situations can be explained by this. If we try to understand these narratives, it can also be an explanation for the different viewpoints in a decision-making process. However, these personal perspectives can undoubtedly create opportunities for cognitive biases in decision making. The thesis of bounded rationality by Herbert Simon (Simon, 1957) states that, the results of our decisions depend on our human and environmental limitations and capacity, how and from where we collect data (quality of data) and how we process them. He says that the result will always be bounded and limited because decision makers will choose the first solution that meets their minimal decision criteria so it won't be the best, it can only be a satisfying one. After Simon, other Nobel laureates like Amartya Sen with the capability-concept (Sen, 2009) or Joseph Stiglitz with the information paradigm (Stiglitz, 2002) also challenged the conventional rational decision makers' thinking. Observing these trends, several social scientists, who were influenced by these new economic models, like Sørensen (Sørensen 1990), or Elster (Elster, 1979, 1989a, 1989b, 1990, 1998) joined this dispute and took very important contributions to the evolution of behavioral economics while they tried to build a bridge between these theories and sociology. Its relevance has been demonstrated in several studies (Busenitz & Arthurs, 2007), (Baron 2006) but the most significant differences compared to the classical economic models which emerged, the uprise of the discipline of behavioral economics was published by Thaler (Thaler et al., 2008) and Kahneman (Kahneman, 2011). Classical economic theories assume an unlimited cognitive capacity without cognitive biases or human weaknesses but when we examine the results of decision-making processes from the perspective of acceptance, we have to admit that the homo economicus exists without roots in reality as Sørensen said (Sorensen 1990). Instead, we should speak about humans (Thaler and Sunstein, 2008) with all these weaknesses but with intuition and two different ways of thinking as emotional intuition (thinking fast) and rational reasoning (thinking slow) (Kahneman, 2011), which can lead to the theory of the predictable irrationality (Ariely, 2008) when "Though not reliably predicted by either environmental concerns or material interests, individual choices around pro-environmental behaviour and resource consumption are, in fact, predictable—they are 'predictably irrational". The most prominent researchers in the field of organizational strategy as Langley and Mintzberg, also examined these trends and they published some important results about that (Langley et. al, 1995) "the decision maker is opened up to history and experience, to affect and inspiration, and especially to the critical role of insight in transcending the bounds of cerebral rationality." If we comprehensively examine the organizational decision-making processes, James G. March's theories are obligatory to observe. When in 1987 he, as an early bird, published the analysis of discrepancies between the actual behavior of decision makers and the recommendations of decision theory (March, 1987) or later, when he took a retrospective look at A Behavioral Theory of the Firm (Augier & March, 2008). But we can find some interesting contributions to the field in Veronika Gustavsson's study (Gustavsson, 2004), who also says "…the entrepreneurial decision-making is not an inborn aptitude but a skill, which is expressed through the adaptable behavior of experts."

In order to eliminate the effect of these cognitive biases, different methods and systems can be used. In this thesis, we investigate the Knowledge-based Expert Systems (KBSs). Supporting business decisions with the help of KBSs and a Knowledge Engineering process can be highly profitable for those organizations or decision makers, who want to have a transparent knowledge base and a thinking path of their decision. In addition, during this process there is chance for exploring a special part of their knowledge, namely their tacit knowledge. According to Polányi's most cited work (Polányi, 1957), there is a part of our knowledge which can hardly be articulated or it cannot be at all, although this knowledge elements are as useful and value creating as the explicit ones. With the help of Knowledge Engineering, this tacit knowledge can be captured and involved in decision making.

Nowadays we talk about smart decisions a lot, but in these cases, we usually think that a smart tool will decide instead of us. In contrast, a smart tool just models the mindset of a smart decision maker, and it can immediately reflect the inconsistency of the decision maker's thinking if it occurs. Actually, when we talk about smart systems, we talk about tools which are able to follow and interpret our own way of thinking, and Expert Systems were exactly like this when those had not been called "smart" as we call them today. If we read Howard Gardner's book about the Theory of the Multiple Intelligences (Gardner, 1983), we know that logical-mathematical intelligence, one of the nine different intelligence introduced, enables us to perceive a symbolic thought and inductive and deductive thinking patterns which can be a real opportunity to build and understand decision models by Knowledge-bases. These studies and opinions opened the door for a new paradigm of decision support with the following essence. "Contrary to the world of IS/ICT there was much less change in the world of decision making. And contrary to the world of IS/ICT we believe that the world of decision making a paradigm shift is imminent. The essence of this paradigm shift is that in the era of knowledge abundance the models based on the idea of scarcity of resources are losing relevance and are bound to play lesser and lesser role. Our research to date shows that in smart decisions the emphasis is on behavioural patterns, behind which we recognize patterns of cognition." (Baracskai et.al 2014). Our assumption, that in similar dilemmas, the knowledge-base of a case could be efficiently used, which tends to confirm the usefulness of this pattern recognition. Perhaps, it will be an innovation in the field of decision support. As Peter Drucker writes about this in his book "Innovation and entrepreneurship" (1985) "Among history-making innovations, those that are based on new knowledge—whether scientific, technical, or social—rank high. They are the super-stars of entrepreneurship; they get the publicity and the money. They are what people usually mean when they talk of innovation, although not all innovations based on knowledge are important. Knowledge-based innovations differ from all others in the time they take, in their casualty rates, and in their predictability, as well as in the challenges they pose to entrepreneurs. Like most superstars, they can be temperamental, capricious, and hard to direct. They have, for instance, the longest lead time of all innovations. There is a protracted span between the emergence of new knowledge and its distillation into usable technology." According to Thomas Khun (1962), the new scientific theories based on individual inventions and discoveries, like knowledge-based innovations, need at least thirty years to become scientific principles.

In this thesis, we want to show how knowledge creation and knowledge exploration can contribute to innovation as its potential source, but we do not want to redefine the concepts of the field. Nevertheless, we think that it is important to define innovation from the point of view of our research. According to Drucker: "Innovation is the specific function of entrepreneurship, whether in an existing business, a public service institution, or a new venture started by a lone individual in the family kitchen. It is the means by which the entrepreneur either creates new wealth-producing resources or endows existing resources with enhanced potential for creating wealth." (Drucker, 2002) But in Christensen's studies, there are two kinds of innovation (Christensen, 1997): sustaining innovation which "targets demanding, high-end customers with better performance than what was previously available. Some sustaining innovations are the incremental year-by-year improvements that all good companies grind out. Other sustaining innovations are breakthrough, leapfrog-beyond-the-competition products. It doesn't matter how technologically difficult the innovation is, however: The established competitors almost always win the battles of sustaining technology" and disruptive innovation which leads to create new markets or value networks by eventually disrupting a current market and value network. As Christensen explains in Harvard Business Review: "Disruption" describes a process whereby a smaller company with fewer resources is able to successfully challenge established incumbent businesses. Specifically, as incumbents focus on improving their products and services for their most demanding (and usually most profitable) customers, they exceed the needs of some segments and ignore the needs of others." (Christensen, 2015) A key point of comparing the two kinds of innovation is that disruptive innovation does not care about existing competitors. In our research, we investigate the results of sustaining innovative projects. But if we would like to understand the conceptual framework of these projects, we can even borrow Prahalad's thought (Prahalad and Krishnan, 2008) "Successful innovations seamlessly connect concepts and ideas to their operational manifestations. We do not present a "charismatic leader" approach to innovation. Neither do we focus on big breakthroughs. We believe that the changing dynamic of markets driven by ubiquitous connectivity, technology, industry convergence (as in computing, communications, consumer electronics, and content), and consumer activism and involvement will create a need for continuous change not just episodic big breakthroughs." But Peter Drucker, as one of the most influential authors of innovation, emphasizes it with his approach when he says: "Most innovation, however, especially the successful ones, result from a conscious, purposeful search for innovation opportunities, which are found only in a few situations. Four such areas of opportunity exist within a company or industry: unexpected occurrences, incongruities, process needs, and industry and market changes." (Drucker, 2002). According to the explanation above, the complex dilemmas examined in this work are the management of the manifestation of a continuous change in turbulent times, and as such, it also means managing the unexpected. Of the gurus quoted above, Prahalad's thoughts are closest to the innovation examined in this study. As Weick says in this regard: "If you want to manage the unexpected, you have to understand, first, how expectations work and, second, how to engage them mindfully… The basic argument is that expectations are built into organizational roles, routines, and strategies. These expectations create the orderliness and predictability that we count on when we organize. Expectations, however, are a mixed blessing because they create blind spots. Blind spots sometimes take the form of belated recognition of unexpected." (Weick, 2007)

1.2. Problem space

As we compare the knowledge background based on the previous paragraphs as available knowledge to some relevant questions as the lack of knowledge, we receive some research gaps which can be summarized in the following problem space (see Figure 1.1) with four pillars and four levels.

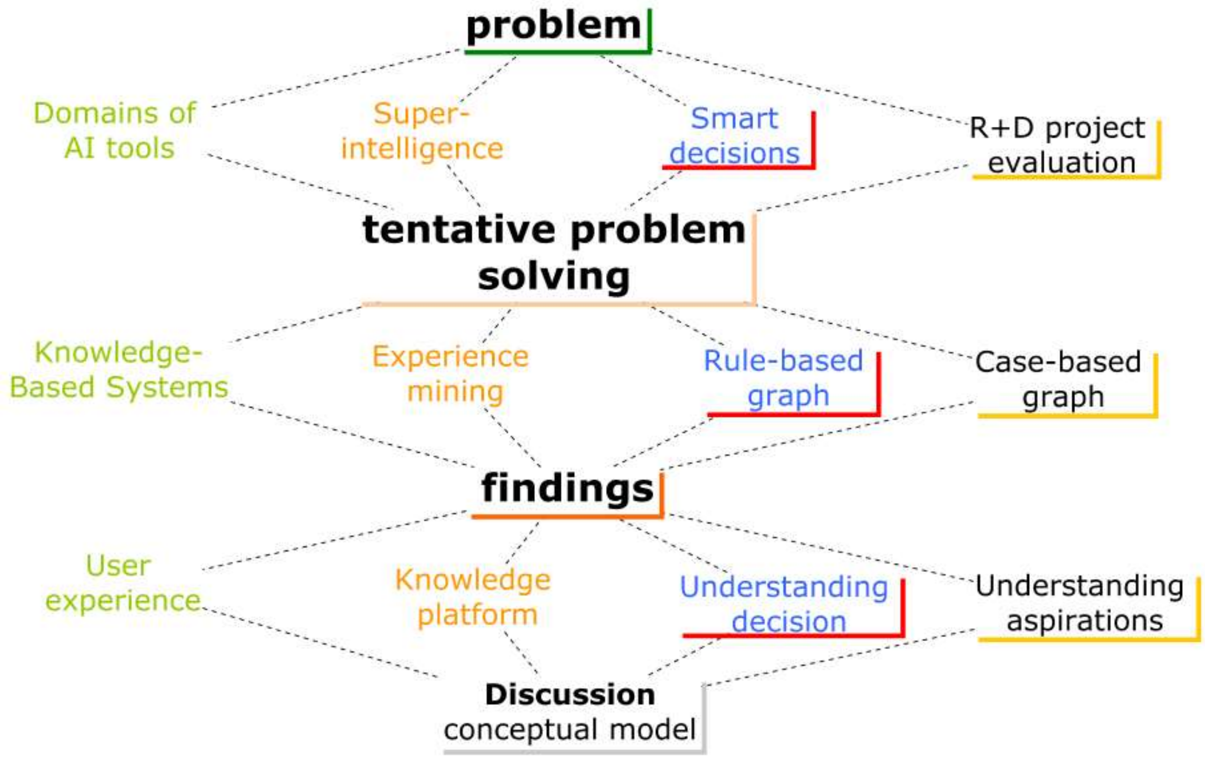

Image source: own research result

Figure 1.1. – Problem space and problem areas with their levels

The skeleton of this thesis is based on two big topic streams: a) the future of the AI-based decision support systems, which will be examined through *"Domains of AI tools*" and "*Superintelligence*" and b) the applicability of these systems which will be investigated by a rule-based reasoning study as "*Smart decisions*" and a case-based example as "*R&D project evaluation*". All these sub-topics have a problem, tentative problem solving and finding levels and as a result of a discussion, we can finally get their conceptual model. In order to understand the future of AI-based systems, we investigated the problem of superintelligence as interpreted by Bostrom (Bostrom 2014) and the history of AI tools and we tried to explain how artificial intelligence will support - and not substitute – the working memory in decision making. This presumes the use of that kind of Knowledge-Based Systems which provide a high-level user experience in the interpretation and understanding of the result of the decision-making process. Our findings will present that when we identify the opportunities and limitations well, we can utilize the acquired knowledge from previous cases and it can lead to "experience mining" which is a new method based on the recognition of *cognitive patterns*. Using these cognitive patterns as an input for a Knowledge-Based System and applying a reductive reasoning on them, we can build a knowledge platform which is able to create new knowledge. As we followed the other topic stream, we aimed to prove the applicability of the Knowledge

Acquisition and Knowledge-based Systems. We presumed that in those cases when the experts or decision makers' knowledge is available, we can support complex dilemmas effectively by KE and KA. During this investigation, the question of how an innovative SME can be supported by a smart decision was defined as a third problem area. Our tentative solution was that Knowledge Engineering and rule-based reasoning will lead to a better quality and transparent result. Our findings were a mindset model and the decision maker's positive feedback about the process. The obvious conclusion from this case is that the decision maker was satisfied with the result, he accepted it, and as he said this manner of support meant a really useful guidance for him in his dilemma due to the organized thinking process. He admitted that he would not have been able to systematize his experience in such an accomplished form without the DSS and the consultancy. Within the fourth problem area, we evaluated R&D projects at a university laboratory with experienced project managers and we built a knowledge-base from the projects as cases. The goals of this process were to know which expectations the project managers have in these projects. As a result, a) we identified the most informative attributes and the logical rules between them, which show the relevant expectations, b) tacit knowledge of the members of the project organization was transformed to adaptable explicit knowledge by systematizing the experience of the individuals.

1.3. The approach

In accordance with the principle of complexity, the problem space above requires an extraordinary approach, since it cannot be solved within a mono-disciplinary framework with only one discipline or with the help of a multi-disciplinary method. Creating and understanding a conceptual framework for the whole, the transdisciplinary approach is appropriate. It means that we have a home - or even we can say that – a host discipline as the decision sciences, but in order to see the big picture from different perspectives we go also beyond some other disciplines, for instance management sciences, anthropology, complex systems or even chaos. We do this because if we examined this complex problem from the framework of decision sciences, we would get a partial or subjective vision of it, therefore, we might think that we observe the reality as it is, even though there is not only one correct answer to our research question. As Basarab Nicolescu writes about this in his book titled From Modernity to Cosmodernity (2014) "Classical binary logic confers its patent on either a scientific or non-scientific discipline. Thanks to this, rigid norms of truth, a discipline can pretend to contain all knowledge within its own field. If the discipline in question is considered as fundamental, as a touchstone for all other disciplines, its scope is thereby enlarge so that it appears to encompass all human knowledge." If we want to visualize the essence of the problem space of our thesis in a transdisciplinary framework, it looks like the model on Figure 1.2.

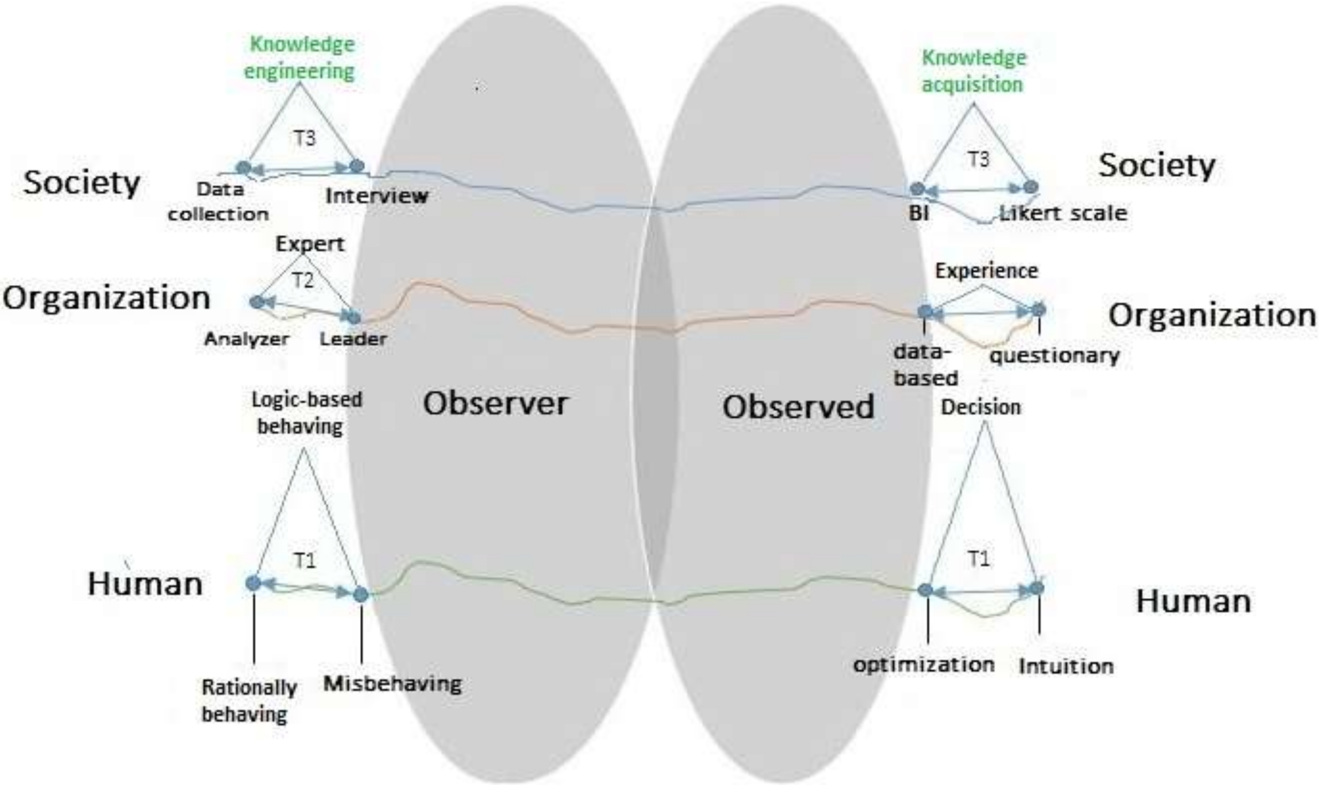

Image source: own research result

Figure 1.2. – Problem space forms a transdisciplinary viewpoint

In order to provide an answer to ontological considerations such as "How do we know that 'the acceptable attribute' is the same for me and for others?" we need to understand the following ontological axiom in relation to the approach of the thesis: "there are, in Nature and society and in our knowledge of Nature and society, different levels of Reality of the Object and, correspondingly, different levels of Reality of the Subject" (Nicolescu, 2010, pp. 24) Understanding the levels of reality, we have to clarify the terms in the sentence above. The Object we observe is the mindset of innovators, can only be examined on a personal level. The researcher (in our case the Knowledge Engineer as an Observer) observes the reality as phenomenon of innovators' mindset.

First, we have to find the correspondence between the external, or we can say the "Object", which is observed from the perspective of the Observer and the internal, which is the Observer or the "Subject". Secondly, we have to determine the level of the Observer because we can see different things at personal or “human” level, at “organization” level and at the level of the “society”. Third, although it may seem commonplace, it is not that at all: there is no a single truth. Statements about the phenomena are in constant contradiction. So, it is not worth convincing anyone of our own truth, instead we need to encourage them to think at different levels. A thesis is a starting point of a statement that seems obvious to a certain person and the antithesis is another statement to the contrary. The synthesis is what derives from the previous two. The opposite of the two statements at the personal level can only be resolved at a higher level, in our case, a new statement can be created at the organizational level. As a consequence, the knowledge engineer reaches the understanding of the phenomenon through knowledge acquisition. This understanding takes place beyond disciplines, so we say that it is transdisciplinary.

1.4. Methodology

As defined by Hakim, our qualitative research provides the “‘individuals’ own accounts of their attitudes, motivations and behavior. It offers richly descriptive reports of individuals’ perceptions, attitudes, beliefs, views and feelings, the meanings and interpretations given to events and things, as well as their behavior; displays how these are put together, more or less coherently and consciously, into frameworks which make sense of their experiences; and illuminates the motivations which connect attitudes and behavior, the discontinuities, or even contradictions between attitudes and behavior, or how conflicting attitudes and motivations are resolved in particular choices made.” (Hakim, 1987) According to the classical distinctions of qualitative data collection methods – as observation, participant observation, interviewing, focus groups and case studies – our research is based on two of them: interviewing and case studies. Knowledge Acquisition is a process which happens step by step from the first level of reality to the next one by interviews. Knowledge bases are built up with the help of experts or decision makers based on their experience by semi-structured, qualitative, in-depth individual interviews. This interview technique allows interviewees in the first part to tell their stories and thoughts in their own words and thus we can learn about the broader circumstances of the cases. Later with focused questions, we try to direct the words to the certain topics that have to appear in the knowledge base. First, in this part of the interview, we also allow the interviewee to use their own terms in the answers and we observe the extent to which they match those previously used by others. If they differ from the terms used earlier, we try to fine-tune and try to find out if the term we offer really has the same connotation for the interviewee. When we make sure it does, we record the answer with the term used in the knowledge base. When we see that there is a need to insert a new aspect or a value in our knowledge base, we try to find the appropriate place for the new element with the help of additional clarifying questions. We finish the interview when we are convinced that the interviewee had told all the relevant facts and circumstances and that all the elements were in the right place in the knowledge base. In case-based reasoning processes, we perform an interview one-by-one with each case provider as interviewees in the first part of the process. After this, we run the reasoning, evaluate the results and usually organize a workshop to introduce and validate the results for the participants. When we carry out a rule-based reasoning process, we usually work with only one decision maker and at least 3 or 4 occasions are needed.

1.5. Papers included, contribution

This thesis deals with a complex system and the complex systems are inseparable. Big picture of expert level knowledge, which was examined, is unrecognizable from the details, but vica versa it works. The overall picture, although, it is not the sum of the parts, is still known from the parts. Once, we have the whole thing, we can define the parts following a well-invented organizing principle. So the first step was to recognize that I would like to get the big picture of the expert level knowledge. After this I identified the four research questions regarding the four scientific papers by which I want to investigate it as:

1) What is the key to better usability of the KBSs?

In paper 1 we examined the history of the systems and 160 different cases to get answer for this question, based on different dimensions as problem domains, business sectors, or even the direction of the reasoning.

2) How can the experts use each other's knowledge and create new knowledge?

In order to get the answer for this question, in paper 2 we studied the knowledge collaboration and organizational learning, innovative communities and knowledge creation.

3) How can expert knowledge be learned from cases?

The result for this question comes from a case-based reasoning example about a project evaluation process in paper 3.

4) How the knowledge of the decision maker can be systematized?

Bringing an adequate answer for this part of the big picture, in paper 4 we present a knowledge engineering process in detail in my fourth paper.

The main part of the dissertation consists of four papers related to the four research questions above. Research questions appearing in these four papers provide the taxonomy of the dissertation.

In paper 1 **(Chapter 2**) titled “Beyond 160 applications of an expert system: key to a better usability”, we give an outline of our experience based on 160 applications of the proposed method and DSS. After a long time and beyond several applications, we believe that we got to know Expert Systems well, and we dare to form an opinion about what the key to a better usability and user experience of these systems is. The goal of this paper is to find the answer for a more detailed question starting from the research question 1): What influences the decision maker's understanding when presenting the results in a Knowledge-based Expert System? We assume that decision makers accept the outcome of a supportive process when they understand and feel that their own thinking is reflected in it. In the first part of the article, we tried to provide a comprehensive picture of the 160 applications in order to prove that our cases come from different problem domains and business fields but all of them are complex dilemmas, thus, these data set is relevant for drawing conclusions. Since this paper is a case study research, it is appropriate to observe and recognize some unique issues. During this research, the focus of our investigation was directed by only one special aspect of interest examined in details: how to understand and accept the result of the decision support more easily. According to the method, in the second part of the paper, we present some case studies individually, identifying the problem, demonstrating some interesting details and the results. Due to the applicability and functioning of the Knowledge-based Systems, we introduce examples for both case-based reasoning and rule-based reasoning. Concluding this paper, we found that the key to the better user experience is that if the result is not a difficult-to-understand interpretation of mathematical derivations with complex formulas, nor it is statistical data visualization obtained from hard management information. The findings confirmed our assumption that a properly designed model graph from which the relationships of the expectations and the logical rules can be clearly read supports the decision. Implications for reasoning and visualization of knowledge at the end of the paper can contribute to the field of knowledge representation and the development and design of Expert Systems.

As a conclusion of thinking about the future of AI tools and superintelligence, we published a conceptual paper about a knowledge platform in paper 2 (**Chapter 3**) with the title

“Collaborative Knowledge Platform: when the Learning Route provides data for the Knowledge-based Expert System”. In this paper, we present a concept of how to build artificial intelligence into knowledge-based systems in order to accomplish experience mining. According to this concept, superintelligence creates the possibility to build a knowledge-based platform in which users can search in each other's knowledge, based on a logical rule-based recommendation, going beyond the solutions of the currently used recommendation systems. Compared to other similar systems, the fundamental difference in this platform is that usage statistics are not primarily analyzed and it does not try to offer content based on simple tagging (such as webstore systems) but tries to map the knowledge of the user based on logical rules and taxonomy and it suggests elements according to that. This platform seeks to make collaboration more efficient by trying to bring the users to a common level of understanding, where every term and phrase has the same connotation for the users. In this conceptual paper, we present the high-level architecture of the platform and how a special AI-based element can be built in, which enables the continuous incremental knowledge engineering of the incoming knowledge elements.

In paper 3 **(Chapter 4)** titled “R&D project evaluation at a university with Knowledge Acquisition”, we show the results of our research in a university laboratory. In this paper, our goal was to illustrate the process by which we built the knowledge base of experience of R&D projects and the final results of the evaluation. In an earlier conference paper (Tóth-Haász et al. 2019), we presented some partial results of the research but in this study we expanded them with an important aspect. In the conference paper (Tóth-Haász et al. 2019), we describe the series of the actions to achieve an acceptable outcome based on our tentative solution after Popper’s study (Popper 1972). According to Popper’s best-known formula of problem solving, the sequence of the events is as follows:

$$P \rightarrow TS \rightarrow EE \rightarrow P$$

where ‘P’ stands for the problem, ‘TS’ stands for tentative solutions, ‘EE’ stands for error-elimination. But this sequence is not a closed cycle because at the second stage, the problem is usually different from the previous one (we can say that the problem has been shifted) since it is another situation which has emerged, partially as a consequence of the tentative solutions which have been tried out and the error-elimination which regulates it. Therefore, the above schema has to be rewritten as follows:

$$P1 \rightarrow TS \rightarrow EE \rightarrow P2$$

This theory was published in Popper's work as: "the traditional philosophical problem of induction". According to Popper's formula, first, we determined the attributes and later step by step tentatively fine-tuned them based on the interviews. Finally, the responses were analyzed by the KBS with the help of the ID3 machine learning algorithm. We describe an interesting fine-tuning and how we recorded the interviews, while the expectations of the participants and values assigned the attributes that evolved step by step. We reveal some interesting details of the narrated stories told by the project managers which led us to our conclusion and let the reader enter the process. The results of the case-based reasoning directed our attention to the difference between projects in industrial environment and in a university laboratory so we started to investigate this topic. In the first part, we consider the relevant literature based on the topics of R&D projects in university laboratories focusing on the researching attitude and academics' motivations, as well as project evaluation methods concentrating on success factors, and finally some thoughts from the field of decision sciences as KA trends and techniques. In order to understand the inner operation of an academic community where the R&D activity happens from the point of view of our research, we examined the *Homo Academicus'* habitus, which was coined by Bourdieu in 1988 (Bourdieu 1988). In this study, we highlight the difference in terms of goals and management between the industrial R&D projects and academic ones. Our findings show that at universities, a reversed process occurs thanks to the *Homo Academicus'* motivation and aspirations, thus in these cases, we can actually talk about D&R projects. This means that in the first part of the project, a development required in order to solve a semi-structured problem, generally initiated from an industrial organization or a laboratory and after that, due to the *Homo Academicus'* scientific curiosity, a research is also launched. In addition, although it seems self-evident that the commitment and passion of project managers is a key success factor of any project, this is especially true for the success of reverse D&R projects in university laboratories. The main objective of this research was to find the most informative attributes in the examined projects and the logical relationship between them related to the research question 3) mentioned above. Since there were not enough hard data from management information systems, we applied a method which was borrowed from knowledge management and decision support, namely Knowledge Acquisition. As a conclusion, we found the three most relevant expectations and three logical rules that can be articulated with them. As far as the research fields concerned, the goal of this paper is to give different understandings of the presented approach of project evaluation and to contribute to the body of Knowledge Management.

In another conference paper **(paper 4 in Chapter 5)**, the results of the decision-making support of a complex business dilemma were presented with the title "If…then scenarios: smart decisions at SMEs" related to the research question 4). In this case study, the CEO of a high-tech SME was supported in his decision on where to place the new business unit of the company. As it was described in the knowledge background part, first we had to know the "story" of the dilemma in order to build the appropriate narrative. So, we started a consulting process during which we learned about the company's background, circumstances and the future plans of the managing director. He had definite ideas and had already tried to think through many aspects of the situation. This is the ideal situation for the decision support presented above, as in the case of a completely clueless decision maker, even the collection and selection of individual alternatives can cause difficulties. This is the essence of smart decisions: only an experienced decision maker can be supported in this way, since AI-based systems cannot substitute the necessary knowledge or intelligence in the process if it was originally missing, it can only help to systematize the existing knowledge. In this case, there were different alternatives in the CEO's mind, both in terms of location and financial construction, as to whether it was worth renting or investing. The proposed method and Knowledge-Based System were the previously illustrated ones, but in this application the direction of the reasoning was different, because this was a so-called original decision when the decision maker does not have prior experience in this decision. This means that, as we mentioned, he has enough knowledge to think through the decision, he knows many aspects of it well, but he faced this specific decision for the first time, he did not have to think about it before. As an outcome of the first part of the process, we gathered 21 attributes and their values in this manner, so we can say that our knowledge-base is sophisticated enough to get a rule-based graph. This graph can be the starting point of that tentative fine-tuning process by which we try to articulate the rules between the elements of the graph. Finally, 231 rules were uttered during the meetings and the rules were refined step by step until no inconsistent elements remained. The result of the rule-based reasoning brought that alternative which the decision maker originally wanted to choose, so it was not difficult for him to accept the result. In order to justify our assumption about smart decisions, at the end of the process, we asked him to give feedback about whether the knowledge systematization helped him. He confirmed that he did not feel pressured towards accepting any of the alternatives, we did not put any non-familiar aspect in his mouth to consider but the process helped him to understand and make his own decision transparent.

2. Beyond 160 applications of an expert system: key to a better usability

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ABSTRACT

We developed our own AI-Based Expert System shell for rule-based and case-based reasoning three decades ago and now there are 160 Knowledge Engineering (KE) process behind us with this system. We hope that this experience give us the right to formulate an opinion about that what is the key to a better usability and user experience in understanding of the result of the decision making process. While we do not think that ES is an omnipotent panacea, we also do not think that its applicability is determined only by the shell capabilities. However, one ability is essential; namely, presenting the result as simply as possible in order to that the decision-maker also can understand it. Our finding is that ES shells are only able to be transparent if they are designed by people who have an understanding of the human thinking process instead of a strong math-based software development approach.

Keywords— Keywords: Knowledge Representation, Knowledge Acquisition, KBS applications, User Interface

2.1. Introduction

Initially, information technology professionals were indispensable in the use of Expert Systems, who spoke machine language (ie. LISP, PROLOG), but were not prepared for Knowledge Acquisition (KA) which required the understanding of the decision problem and the decision maker’s reasoning. In the second half of the eighties, ES shells appeared, which no longer required information system specialists during the decision making process but knowledge engineers. They had a different role in the knowledge acquisition process because they had to place at least as much emphasis on understanding the decision-maker's mind as getting the software data into the software properly. After three decades of experience and over one hundred and sixty applications, we believe that we understand ESs, and we can form an opinion about that what is the key to a better usability and user experience of a Decision Support System (DSS). We tried to find an answer for the research question: what influences the decision-maker's understanding when presenting the results in a Knowledge-based System (KBS)?

One of the most widely acceptable definitions of expert systems, however, was given by Edward Feigenbaum from Stanford University. He defined an Expert System as “an intelligent computer program that employs knowledge and inference procedures to solve problems that are considered difficult enough to require significant human expertise for their solutions” (Feigenbaum 1981). During the evolution of decision-making discipline, somehow the examination of reasoning and the transparency of the whole process was always ignored. Results of operational research had a great impact on the development of decision-support tools. Meanwhile the developers of this tool haven’t even thought of the process of human reasoning.

Nowadays we talk about smart decisions as a form of complex problem-solving a lot, and the layman might think that in these cases a smart tool, for instance a KBS, will decide instead of us and by this, it save us from the often overwhelming task of making complex decisions.

Actually, we do make smart decisions ourselves as well, but we need those kind of tools which are able to follow and interpret our thinking in these processes. ESs, and within them KBSs can be such if they ensure that the results are easy to understand in the form they are presented and there is no need for complicated demonstration of the results based on an ambiguous appearance.

2.2. Literature review and theoretical background

We examined the existing literature as a background to this study on four key areas due to their relevance to KBSs and their applications:

- how they represent the explored new knowledge,
- KA as a method to prepare knowledge for systematization,
- applications in the field of KBSs,
- user interface of KBSs from the aspect of human-computer interaction.

Knowledge Representation (KR)

Knowledge has become the main value driver for modern organizations and has been described as a critical competitive asset. An important feature in the development and application of knowledge-based systems is the KR. The aim of knowledge representation is to facilitate effective knowledge management which concerns expressive representation and efficiency of reasoning. Opponents of expert systems argue that machine learning never can replace human reasoning. The essence of KBS is to make the decision maker's reasoning transparent, therefore we argue that "transparency of reasoning" is a functionality which can help the decision maker.

It seems both most of the earlier and the recent published papers bring case studies and examples for this process from medical expert systems (Santra et al. 2020)(Kong et al. 2008)(Boegl et al. 2004), although the problem of the easy to understand knowledge representation is not limited to that area of use (Chau & Albermani 2004)(Hatzilygeroudis & Prentzas 2004a)(Pereira et al. 2019). Doctus KBS shell, which was used in our research, belongs to the area of symbolic systems, this means that the knowledge representation it uses is based on symbolic logic in the form of "if… then" rules. A knowledge-based system consists of two main parts: the software tool called the shell, which contains the inference engine but is empty in terms of the content and the knowledge base, which is the representation of the expert knowledge." (Velencei et. al, 2014).

Knowledge Acquisition (KA)

Our approach is that, KA occurs when the knowledge engineer attempt to acquire the domain experts' explicit and tacit knowledge (Polanyi, 1958). When the knowledge engineer is successfully in this process then KA is an adequate method for building knowledge-bases from the experts' knowledge and experience. Shaw and Woodward's study (1990) advocates a "patchwork approach" which can bring still valid solution for the listed. Partially similar proposed KA techniques were also presented by Boose three decades ago (Boose, 1989). Some studies examined the trends of this long period: Wagner's review paper is based on Boose's often cited study (Wagner, 2017). Kidd's book (Kidd, 2012) and Zaraté's study (Zaraté and Liu, 2016) give some useful suggestions in the field of KA and decision support systems. Their findings meet with the approach of our research. Studer's study (Studer et al., 1998) presents the relationship between KE and the types of Knowledge-based Systems like the one used in our research, and gives an overview of the development of the field of Knowledge Engineering. That paper "put the emphasis on the paradigm shift from the so-called transfer approach to the so-called modelling approach. This paradigm shift is sometimes also considered as the transfer from first generation expert systems to second generation expert systems."

Knowledge-based system applications

As we analyze the existing literature in this field we can find that most of the applications bring solution in some typical problem domain as HR, investment, or R&D and the processes happened in companies which operate in typical industries as telecommunication, manufacturing or oil and gas. Segments of these give the field where is worthwhile to apply knowledge engineering and KBS. These are the ones which are complex enough that human thinking already needs help to remain consistent. Our cases examined confirm these observations.

User interface

Just like any software tool, the success of using an expert system depends greatly on the user experience, in this case on that how can help the user interface to understand the result of the decision making process. When we apply the Knowledge-based System shell, it almost seems like participants of the decision-making process engage in conversations with the computer, as a high level form of human-computer interaction, because it uses concepts defined by the participants themselves. During this process conversations with the computer constrain the user to clarify the different meanings and connotations of the used concepts.

We can find some descriptive studies which give implications of how to develop easy to handle KBSs (Berrais 1997)(Su, Liu & Hwang 2001) but there are still research questions to explore in the problem space. In the last decade a significant part of the relevant literature approaches from the perspective of human personality types and their associated personality traits (Su, Chen & Shue 2011)(Alves, Natálio & Henriques-Calado 2019)(Gajos & Chauncey 2017) and these studies call for providing user interfaces adapted to individual characteristics. But these papers broadly also agree that the design of interface can make a significant contribution to the need for cognition.

2.3. Methodology and dataset

The continuous improvement approach of development of KBS was mainly affected by our experience acquired through real knowledge engineering processes in many business fields. We tried to get direct feedbacks from those decision makers along our consultancy work, who were interested in how they can explain their own decisions and how they could make the decision-making process more transparent. After presentation of the results of a successful decision, we tried to understand what might be the reason why they still couldn't explain or understand how that decision was made. In order to get answer for our research question, we examined our knowledge engineering processes with the method of case study research. Case study research can be a relevant way of observing and recognizing natural phenomenon, even around any unique issues, that exists in a given dataset (Yin, 1984). Unique issue means that only a special aspect or number of subjects of interest are examined in details. But we can find another comparative essence for definition of this methodology as “unlike quantitative analysis which observes patterns in data at the macro level on the basis of the frequency of occurrence of the phenomena being observed, case studies observe the data at the micro level.” (Zaidah 2016)

Based on Yin’s study we can distinguish three categories of case studies (Yin 1984), namely exploratory, descriptive and explanatory case studies. In accordance with the definitions of these categories our case studies belong to descriptive, because our case study research addresses either a descriptive question like “What is happening?” or an explanatory question like “How or why did something happen?” The purpose of our investigation to collect descriptive and factual data systematically, to interpret the data, summarize what was found, and draw reasonable conclusions.

From the direction of reasoning we have to differentiate the Rule-based Reasoning (RBR) and the Case-based Reasoning (CBR) cases. In the first version we try to find the most satisfactory alternative out of the few possible as a deduction, while in the second one we look for the some informative rules and attributes based on the cases as inductive reasoning. Within our research we examined 93 cases as RBR and 67 cases as CBR. In 51 cases from the RBR cases we could articulate more than 800 rules, and these were classified as expert level. In 42 cases only less than 250 rules were uttered, these were labelled as beginner level. In the CBR instance the number of cases was the basis for qualification: we have 28 examples where we made the reasoning from more than 40 cases and 39 where we made it approximately from a dozen.

Over the above mentioned classification other segments of our dataset would be interesting based on business sectors as telecommunication, automotive industry, pharmacy, public, trade, energy, sport, finance, and problem domain as evaluation of investment, financing, R&D, or HR. As aggregating the cases we can see that CBR is more common in R&D and HR decisions while RBR is more typical in investment and financing decisions.

Generally in relation to each sample we can say that during a successful knowledge acquisition process at least 15-20 relevant attributes are articulated and at least 3-4 different values must be assigned to each attributes, since in order to make a systematized knowledge-based decision the set of well-ordered preferences is required. In those cases where there were too few attributes in the knowledge-base, we could not state that the expectations are structured enough sophisticatedly, and thus a chance made for significantly impact on the outcome of the process caused by the individual's cognitive biases.

2.4. Case studies for reasonings

Rule-Based Reasoning

When the expert articulates the important aspects of the decision as well as the rules, the system triggers these rules to get the evaluation. We call this as deduction or Rule-Based Reasoning. It is useful when the decision maker does not have experience in the domain, and the situation calls for original decision. KBS supports those decision makers who are experts in their decision domain. As a finding we experienced that beginner can articulate couple of dozen rules, while experts can couple of hundreds but we had a unique case when the expert defined 1800 rules.

In order to demonstrate a complex business dilemma and the process supported the decision we present a case study. It is an enterprise company, which employs 60,000 people, and it was developed by vertical integration of the department of forestry or woodworking or even designing hotels. The holding organization deals with development, IT and investments. As most of the factories were located in developing areas, they received financial support for investments that increased the level of employment within the company. In contrast, the company's strategy was based on expanding existing foreign markets. This contradiction caused a lot of issues and problems in the management. Certainly, this dilemma required to change the strategy and we supported the decision which targeted the selection of the best strategic way. The first and most important step was to collect the used terms in strategic planning while those should have the same connotation for everyone in the process. This was facilitated by many discussions and semi-structured interviews, during which the conceptual differences between the experts and the decision-maker were clarified. What happened in these interviews? Knowledge gathering, knowledge acquisition. Transforming explicit and tacit evaluation criteria to soft data. Clarification of the used terms. What happened when the knowledge base was building? A common understanding the correct use of terms as a synthesis of the experts' viewpoints. It was understanding the new knowledge by interpretation of explicit rules. The main purpose of the decision-making process was to examine that the different competing strategies (as possible alternatives) what kind of challenges would bring to the operation of the company. The primary goal of the company, of course, is sustainable operation. This can be achieved if it has the characteristics of stability of operation, stability of growth and flexibility.

After defining the attributes and their values we can build a rule-based graph, which represents the hierarchy of the attributes, therefore a transparent representation of the decision makers reasoning. The deductive graph describes the dependency relations of the attributes. The conclusion attribute on the top of the graph. Attributes which do not depend on anything are called input attributes, or independent attributes. Attributes depending from other attributes are called dependent attributes.

The first two levels of the decision tree (goals and attributes) are similar for all companies. The first three levels come from the leader, the fourth level is from the managers. For example, we can support flexibility by reducing the exposure to manufacturing technology, suppliers and customers. These goals can be bring down into criteria, such as "independence from customers" can be break down to "share of the large customers" and "number of new customers". The values of these are determined by rules given by the decision taker, domain expert.

Viability as ability for surviving can best described by three metaphors: we used animal names. Although, maybe it not seem serious, the reason is that the exact terms and definition for this have not yet been existed in the organization and it was easier to understand in this way. Both the lion and the donkey are viable, but differently

	Flexibility	rigid	flexible
Stability (growth)	**Stability (operation)**		
weak	weak	donkey	lizard
weak	strong	bull	rooster
strong	weak	bear	fox
strong	strong	elephant	lion

Table 2.1. - Rules of sustainability

Both the lion and the donkey are viable, but differently. The model and set of the rules derived from it presents the idea as

"If your company is flexible, and if the operational stability is strong, and if value growth stability is strong, then the company is like a lion." According to the rules above the company could have been elephants with a market expansion, if they had neglected flexibility. In that situation if they had increased their raw material sales to some new customers in the Middle East or even existing in the West, they would have been equally dependent on the market. They

did not have the opportunity to expand in America, because they were already in a loss-making situation.

Case Based Reasoning (CBR)

If the domain expert has enough experience (a few dozen cases to evaluate), he can articulate the criteria, but neither can determine their importance in relation to others nor the rules between them by induction, which is a symbolic version of case studies. As there is an extensive experience in the domain, the situation is described as routine decision. After the attributes and their values are defined, the next step is to collect the cases, including the outcome of each of them. Cases can be anything that we can describe from all important aspects (i.e. defined attributes). One value of every attribute is assigned to each of the cases. The KBS is for discovering the rules, which describe the cases according to the expert's experience. The result of the Case-Based Reasoning is the Case-Based Graph which can visualizes the rules induced from the cases. To build the Case-Based Graph the attributes are taken one-by-one to form subsets according to their values. In this system the strength of attributes is listed in an entrophy-gain based list - is was mention above as informativity – and we try to get the most informative attribute. The most informative attribute is the root of the graph and the first level subsets are formed according to its values. These subsets are further divided using the same algorithm until all subsets are homogenous by benchmark values.

Demonstrating the application of CBR we also present a relevant case study. Recently we evaluated 21 engineering R&D projects in a university lab with the project managers to get to know what have the strongest impact on the successfulness of the projects. In the knowledge base 16 attributes were collected and 3 or 4 values were assigned to each of them (Tóth-Haász el al. 2019). The obvious advantage of a case-based knowledge base is that attributes can be ordered based on their informativity and then reduced to the most informative ones. In our case study the informativity of the attributes can be seen on the table 2.2.

Attribute	Informativity
the team leader's relationship to the topic	0.3439
project manager's experience in the domain/topic	0.3196
project manager's character	0.2596
problem definition	0.2355
prior knowledge	0.2299
project manager - team leader communication (2)	0.2170
timeframe	0.2118
source of the idea	0.2025
project manager's experience in coordination	0.1973
aim of the project	0.1841
project manager change	0.1814
customer	0.1671
relationship between project manager and customer	0.1592
the team leader's capacity	0.1482
constitution of the developer team	0.0708

Table 2.2. - Informativity of the attributes

The greatest benefit of the building a case-based knowledge base is less obvious. This process is almost always accompanied with knowledge discovery. It is very common when the case-providers or experts are surprised at the first sight of the Case-Based Graph and get a deeper understanding of rules as the visualized results of the process. From the result of induction, the important aspects of the decision can be determined using reduction, by extracting the rules from the Case-Based Graph. In our case study the most informative attribute is “the team leader’s relationship to the topic” at the top of the list (table 3). According to this based on the result of the evaluation we can articulate the most informative rules as:

- if “Project manager’s experience in the domain/topic” was “master”-level, but “the team leader’s relationship to the topic” was “forced to commit”, then the result of the project was “financial failed”;
- if “ Project manager’s experience in the domain/topic” was “master” or “advanced”-level and “the team leader’s relationship to the topic” was “accepted”, then the result of the project was “according to the agreement” ;
- and it is very interesting to note that if “Project manager’s experience in the domain/topic” was “beginner”-level and his or her “experience in coordination” was also “beginner”-level but “the team leader’s relationship to the topic” was “enthusiastic” the result of the project was “according to the agreement”.

It was a surprising result for the participants of the evaluation process, because as they told that in the workshop organized to introduce the result, this was on their tacit knowledge but they were not able to articulate earlier.

2.5. Discussion

During our knowledge engineering processes we worked with different sized companies and organizations helping their experts achieve transparency of their reasoning. Our experience spans many areas and fields from decisions concerning investments, software implementations, human resource management or even R&D decisions.

Implications for reasoning

During our decision-making processes supported we found that, less attributes are enough in the case-based reasoning processes because the decision-maker has prior experience and his or her expectations are cleaner while in rule-based reasoning processes which are original decisions they are not able to articulate such appropriate. Another finding is that when only one expert was involved in the decision-making process, so only his or her mindset had to be modelled, there was always less inconsistency in the rules than when more experts were involved. This proves that a decision from only one mindset is always more consistent than a decision from multiple mindsets. During the multi-expert processes it was possible to visualize the contrast between the way of thinking of experts from different fields (such as production managers or sales managers). This can provide an opportunity for a decision maker from a certain business field to use the special considerations of an expert in another field.

These findings motivate us to call for a new way of utilization of reasoning. Most of the KBSs are suitable for text or data mining, but we encourage experience mining. Experience mining is a new method together with a KR technique by integrating symbolic logic and artificial neural networks and by creating a new machine learning algorithm, which enables the system to convert the results of case-based reasoning (Richter, 2009) into a new rule-based knowledge base (Baracskai, Velencei & Dörfler, 2005). From a practical point of view this means that KBS can be adapted to recognize behavioral patterns and these patterns can later be searchable and useful in similar decision making processes by giving new perspectives and ideas for the decision-makers.

Implications for visualization of knowledge

Design of surfaces of KBSs addresses the issue how to combine the up to date user experience and user interface (UX/UI) trends with special goal of the process: understanding the new knowledge. The primary measure of whether design of the system is easy-to-handle is that the user should be able to use it individually (because fundamentally, role of the knowledge engineer is not to handle the system). Since the users become familiar with the software development trends, applications are increasingly intuitive, hence, according to these trends the surface of the system should be organized as simple as possible and should be very graphic. It is recommended to involve a knowledge engineer in the design of the knowledge visualization or user interface who can bring the view of decision-makers mindset based on many case experiences.

Research limitations

Regarding the limitations of our research we identified a phenomenon many years ago that defines the field of decision support systems. Most of these systems included DSSs and KBSs are developed using two approaches. One of these is when academic researchers launch a development with the primary purpose of research or proving some kind of theory and in these cases a higher user experience as an expectation is almost entirely ignored. The other is when software designers and programmers develop an application mostly for business purposes to support a certain type of dilemma (most of the examples found are for medical decision support). The results of these decision support systems and their exact description are typically not published as research findings by the developers, thus it is difficult to compare to the first group. The future direction of our research can be defined as the development of a comparative method that attempts to evaluate the two groups on the basis of a homogeneous set of criteria.

2.6. Conclusion

The main purpose of this paper was to give some ideas for knowledge engineers and KBS developers to achieve a higher user experience in the knowledge engineering and decision making process. We believe that, by this we can contribute to a wider spread of application of KBSs and beside the rise of the data-driven decision support experienced in recent times (Logg et al. 2018) this overshadowed field of the decision sciences can be a real choice again.

We hope that this article open the door for a new way of thinking about these systems, and which perhaps is more important, for those decision making processes when the potential of experience and knowledge can be exploited.

3. Collaborative Knowledge Platform: when the Learning Route provides data for the Knowledge-based Expert System

Working paper:

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ABSTRACT

The Digital Age has brought not only new tools but also several new methods. A Collaborative Knowledge Platform with a hybrid intelligent system may be the appropriate base of a knowledge management system to ensure inspiration and new knowledge for a professional group of individuals who work for an innovative organization. The method involves combining machine learning algorithms with if-...then logical rules and the result can be the transformation of personal knowledge – and tacit knowledge as a part of it – to widely adaptable explicit knowledge. Individuals can learn informally while their learning route will supply the most adequate data for a reductive reasoning process, which finally leads to experience mining. In this paper, a concept and an approach are suggested to improve the knowledge collaboration in innovative communities; and a tentative process of creative problem solving will deliver the results in the development of a Knowledge Management System.

Keywords:

Knowledge Collaboration, Innovative communities, Knowledge-based Systems, Knowledge Management Systems, Experience mining

3.1. Introduction

There are many organizations or inter-firm collaborations (Hung, Kao & Chu 2008) where innovation and knowledge creation are two of the most important goals in order to reach or keep the cutting-edge position (Segercrantz, Sveiby & Berglund 2016). Several studies confirm the effects of knowledge-sharing and learning behaviors on performance of a firm (Law & Ngai 2008) (Fu, Diez & Schiller 2013) (Asrar-ul-Haq, M. & Anwar, S. 2016) or the positive correlation between knowledge management practices and competitive advantages (Nieves, Quintara & Osorio 2016) (Lee, Foo, Leong & Ooi 2016). ISO 30401 as a recently appeared strandard of Knowledge Management also ‘considers that knowledge management is a holistic approach to improve learning and effectiveness by optimizing the use of knowledge, in order to create value for the organization’ (Maximo et al. 2020).

The innovative communities struggle with the problem to find an appropriate method to spread or even target the relevant information and knowledge in an effective way within a definitely knowledge-oriented community (Chui et. al. 2013) even if it was in different places or units (Tortoriello, Reagens & McEvily 2011). ‘Relevant’ is a very emphasized attribute because as experts say (Velencei, Szoboszlai & Baracskai 2014) universities usually do not deliver the knowledge which can be instantly implemented in on-the-job contexts but they prepare their students for the basics of disciplines. Education at universities is not ‘knowing-oriented’, thus there is a gap between ‘to know how’ (knowledge from the university) and ‘to know when’ (on-the-job context in an organization). There is a need for a problem-solving method to bridge the gap between ‘to know how’ and ‘to know when’, therefore an emerging research can bring a solution to find the building blocks of this transformation. In this ‘bridge’ - or we can even call it Collaborative Knowledge Platform - every member should get the opportunity to have access to all kinds of information, ideas or inspirations by knowledge collaboration which can be adaptively embedded into their prior knowledge in order to get benefits from using the platform (Phan, McNeil & Robin 2016) and fulfil the final goal of organizational learning for the common good (Ricciardi, F., Cantino, V. & Rossignoli, C., 2020).

In accordance with the principle of complexity, this problem requires a transdisciplinary approach. As Basarab Nicolescu writes about this in his book titled ‘From Modernity to Cosmodernity’ (2014) “Classical binary logic confers its patent on either a scientific or non-scientific discipline. Thanks to these rigid norms of truth, a discipline can pretend to contain all knowledge within its own field. If the discipline in question is considered as fundamental, as a touchstone for all other disciplines, its scope is thereby enlarged so that it appears to encompass all human knowledge.”

3.2. Literature overview

Obviously, learning in the CKP can be highly profitable for people who work as knowledge-workers for a new type of organizations (Drucker 1988) but at the time of the high-tech firms and other innovative organizations, there are several individuals who are educated but semi-specialized human resources of the company. These knowledge workers own the intellectual capital of the corporations thus the organizations need to take care of letting these people get a special possibility to renew their motivation and their knowledge (Davenport (Garcia-Penalvo & Conde 2014). Many studies have confirmed that people learn in very different ways (Labib, Canós, Penadés 2017) (Galanis, Mayol, Alier & Garcia-Penalvo 2016) (Noe, Tews, Marand 2013) and the digital age has brought a large variety of informal learning methods (Brown 2000; Brown, Dehoney & Millichap 2015) through social communication tools (Leonardi 2014), (Biasutti 2017) and the newest mobile technologies (Sommerauer & Müller 2014) even in collaborative learning (Wang et. al. 2017). George Siemens (2005) relevantly summarizes the significant trends in learning and according to him, learners will turn into a lot of different things which may be not related to their current job, a variety of ways of the informal learning will be more relevant in their continual learning process which will last for a lifetime and the technological tools will determine their thinking about learning. He says that "the organizations and the individual are both learning organisms…the increased attention to knowledge management highlights the need for a theory that attempts to explain the link between individual and organizational learning." He emphasizes the importance of 'know-where' (the understanding of where to find necessary knowledge) over 'know-how' and 'know-what'. This trend leads to that phenomenon which is described, among others, in Nicholas Carr's book titled 'The Shallows: What the Internet is Doing to Our Brains' (Carr 2010) Nowadays, learners' continuous access to the internet has changed the way of gaining information and knowledge making it easier now than ever before. Questions are answered immediately with the help of Google or other search engines. This has obviously changed the method by which students accomplish their assignments. However, the reliability of the easily accessible information is uncertain and their knowledge can be shallow. The two-way communication is very important because the participants of the professional community need the immediate and targeted interaction to get answers for their questions in informal learning. The emphasis is on the 'interaction', because the members learn from each other by knowledge sharing as the key success factor of the Knowledge Management Systems (Kang, Lee& Kim 2017)) although the approach of knowledge-sharing networks is challenged (Liu, Ray & Whinston 2009) and by knowledge collaboration examined as the theory of process, mobility or synergy (Cheng & Chang 2019). If we consider the new-generation systems and tools which support these learning processes, we can examine the Massive Open Online Courses (MOOCs) in the last decade with other solutions listed by Foray & Raffo (2014) or Communities of Practises as sources of innovation capabilities (Choi, Ahn, Jung, & Kim 2020). These struggle with a real challenge to offer the most relevant and personalized content as potentially useful personal knowledge resources (Zhen, Song & He 2012) – but most of them can offer commonly used content which can be manipulated (Prawesh & Padmanabhan 2014). The difference between these two methods from the aspect of learning methodology is validity. When a large group of users download or use a piece of content very often then a pure arithmetic-based engine, which most of the recommendation systems use, promotes 'the most viewed' or 'the hottest' content without relevance examination based on logical rules of the learning route. It means that the most used content will be recommended, hereby it may not be the most relevant for an individual in a certain problem-solving situation at all. Although there are some researches which attempt to make progress in this issue (Wu et. al 2016) (Tarus, Niu & Yousif 2017) (Christudas, Kirubakaran & Thangaiah 2017). In several studies and initiatives, we can read about the fact that the conventional Learning Management Systems (LMSs) actually manage only the administration part of learning such as lecture materials, course and topic descriptions, intended learning outcomes, grading information and so on but they do not manage the learning process itself. As we can read it in an educational initiative published in 2015 titled "The next generation digital learning environment" based on a research by The Bill and Melinda Gates Foundation, the specific recommendations for the next generation LMSs, among others, are interoperability, personalization (instead of uniformity and centrality), and cloud-based and mash-up architecture. Accomplishing all these recommendations means a great opportunity in and of itself, but when we want to place this at the service of knowledge collaboration, it is a particular challenge that will lead to a new approach to build a knowledge management system based on a next-generation LMS. The other problem with the conventional corporate universities regarding the contents is that in many cases these virtual places do not offer interesting and inspiring content, only mandatory and official information such as corporate governance regulations or a list of corporate phone numbers. Actually, these systems are very similar to a file server structure with a corporate design, and thanks to this, the creative individuals often look for opportunities for learning and knowledge collaboration outside the corporate space during a problem-solving process. Possible solutions for facilitating this learning are published in a study by Oh & Han (2018). In some cases, the reason is that the employees are afraid of their boss's opinion about these conversations or there is not any opportunity for the spontaneous virtual team work. Although there are some examples published by Huang and Liu (Huang & Liu 2017) when the social media sites are used as a work-related utility but in these situations the company loses the chance for acquiring its employees' knowledge capital but at the same time this particular benefit appears for Facebook or other social sites.

Over the mentioned facts, the most unique goal of the CKP is to attempt to transform and formalize the users' tacit knowledge elements, which was originally introduced in Polanyi's work (1958). Although, the role of tacit knowledge is emphasized in some studies as an important aspect of innovation capability (Smith 2001; Cavusgil, Calantone & Zhao 2003), it is hard to make it explicit and applicable (Faraj, Krogh, Monteiro & Laghai 2016; Tsoukas 2002).

3.3. Collaborative Knowledge Platform (CKP)

In a heterogeneous knowledge community where creative problem solving happens, such as at innovative companies, or in R&D laboratories, it is important to enable the members to join the platform based on their preferences, requirements, their own knowledge-level to encourage epistemic curiosity (Hardy, Ness & Mecca (2017), nevertheless there is some evidence for the integration of creativity into the learning process which also sustains students' engagement in participatory learning programs (Liu, Chen, Ling & Huang 2017) . We can see in Fig. 3.1. how the different user groups can reach the platform.

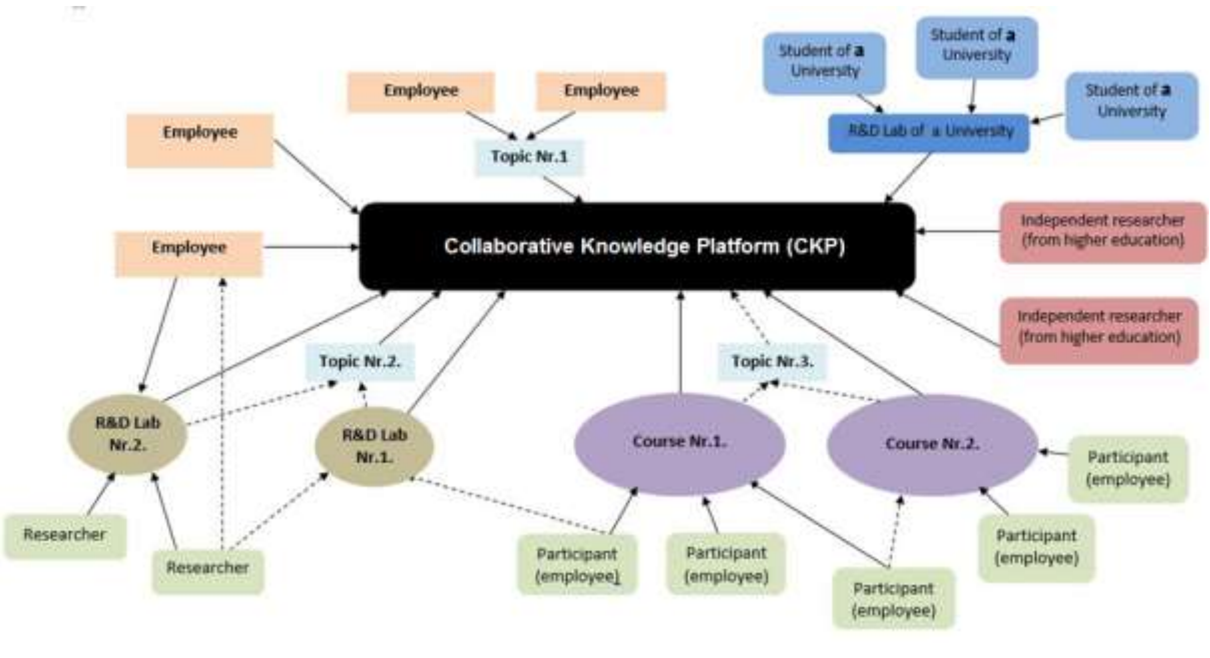

Image source: own research result

Figure 3.1. - User groups and their relations in the CKP

Obviously, we cannot require anyone to identify themselves with the values of the organization by reading a whitepaper about it or by watching a short video with the chairman who might have never met the employee. But if there is an interesting topic about the same value on the company's knowledge collaboration platform and every member of the knowledge community has an opportunity to create and post their own content in connection with it – it means that they can upload images, links, videos or even funny memes – it may bring the topic closer to them and it contributes to the development of an organizational learning narrative (Burnett, Grinnall & Williams, 2015). Gould and Powell in their study (2004) attempted to understand the nature of organizational knowledge in supporting decision-making systems, which can be useful to explore a part of the problem domain.

Evidently there must be a content curator whose task is not to administrate the user information and authorizations, but to analyze the informal network learning (Schreurs & Laat, 2014) and to facilitate learning as well. The curator's role is very important on the CKP, we can say he or she is one of the fiduciaries according to Iwai's theory (2001) inasmuch as he or she can be titled Chief Learning Officer or Knowledge Manager with an essentially fiduciary mandatory. This role is responsible for the consistency of the taxonomy behind the whole platform, each content should fit into the "big picture". It does not mean tagging the content elements but it means to support the automated Knowledge Acquisition (KA) process. Implications for KA techniques were presented as a descriptive study by Boose (1989) almost three decades ago. Based on that paper, Wagner recently investigated the trends (Wagner 2017) in the field of KA since then and he has found that the automated Knowledge Engineering (KE) and modelling are the two most increasing methods (see Fig.3.2).

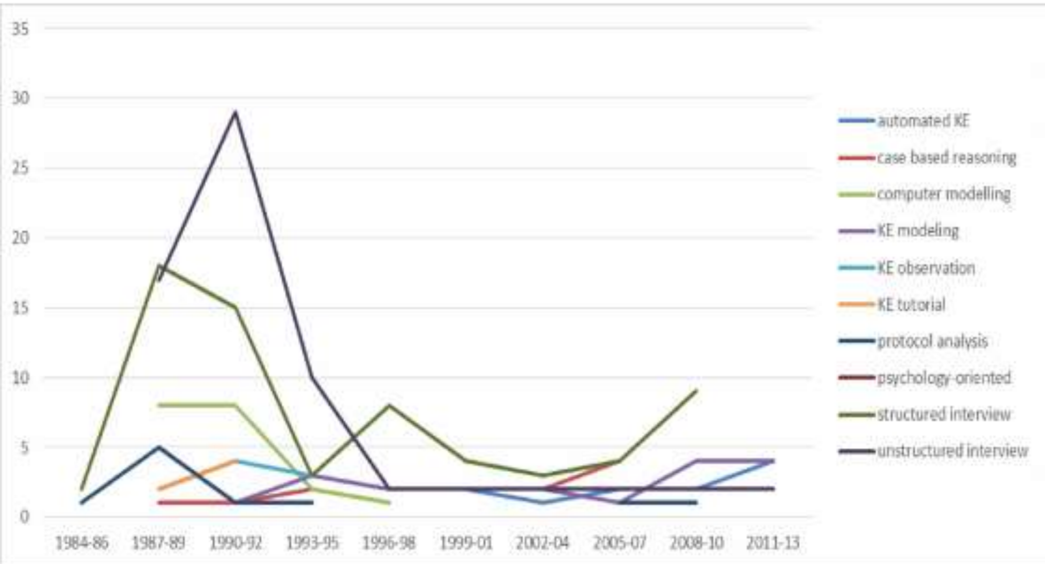

Image source: Wagner (2017.) Expert system KA techniques over time

Figure 3.2.- Expert System KA techniques over time

We can find some examples for the application of these methods as a basis of new methodologies (Curran et. al 2010). Our suggestion to use these techniques as the KA process can be seen in Fig.3.3. below.

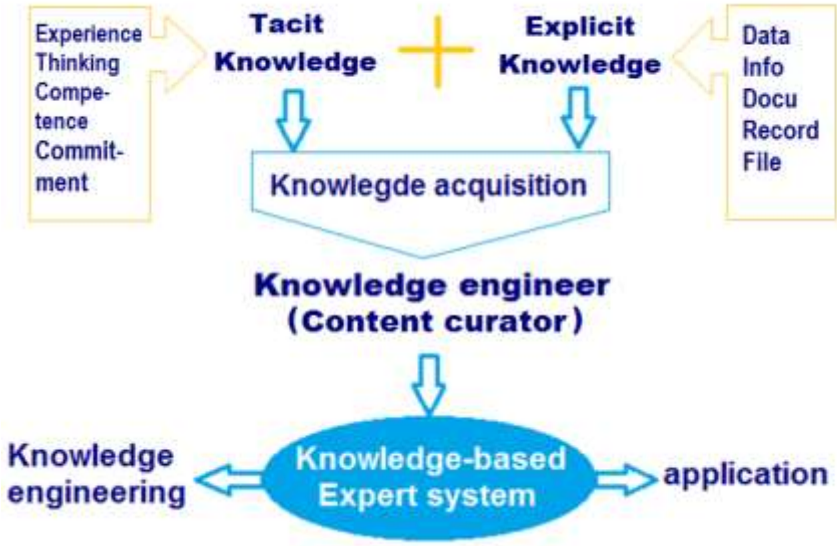

Image source: own research result

Figure 3.3. - Knowledge engineering process in the CKP

As published in Shamina and Starodubtsev's recent study "Content curators fulfil the important didactic, analytic and research, as well as compensatory functions, reducing overhead and forces of other users to find relevant information. Personal knowledge management (PKM) is considered as the basis of the content curation" (Shamina & Starodubtsev 2015) therefore the curator fulfils the role of the knowledge engineer in this process.

Corporate universities are very influential professional and strategic communication channels to the employees beyond the learning perspective, thus the comprehensible and systematic contents and their taxonomy should be handled with high priority.

In this virtual learning environment not only the contents but also their usages are bases for logical rules to systematize the knowledge in the system by artificial intelligence. Users of the system supply the machine learning and the collective knowledge base behind the system as a core component of the Knowledge-based System (KBS) in direct and indirect forms as well. The direct form is that when users upload or download contents, which can be any kind of artifacts as documents, videos, podcasts, or pictures, and they share it with an authorized circle. The indirect form is that when the members of the knowledge community use or even ignore to use some certain contents or their elements, in this case the patterns of the usage are the manifested data. Every interaction generates input into the knowledge base, so individuals contribute to the common knowledge creation without an explicit purpose when they repeatedly pause a video file at the same point or share it with a recurring keyword in the comments. In this case the keyword given by the commenter users may be more relevant than the original one given by the author. The unstructured data, collected as part of the knowledge acquisition of the process, get into the Knowledge-based System, which is a built-in core component in the mashup architecture of the platform (see Fig. 3.4.), in order to make the typical thinking and behavioral patterns recognizable.

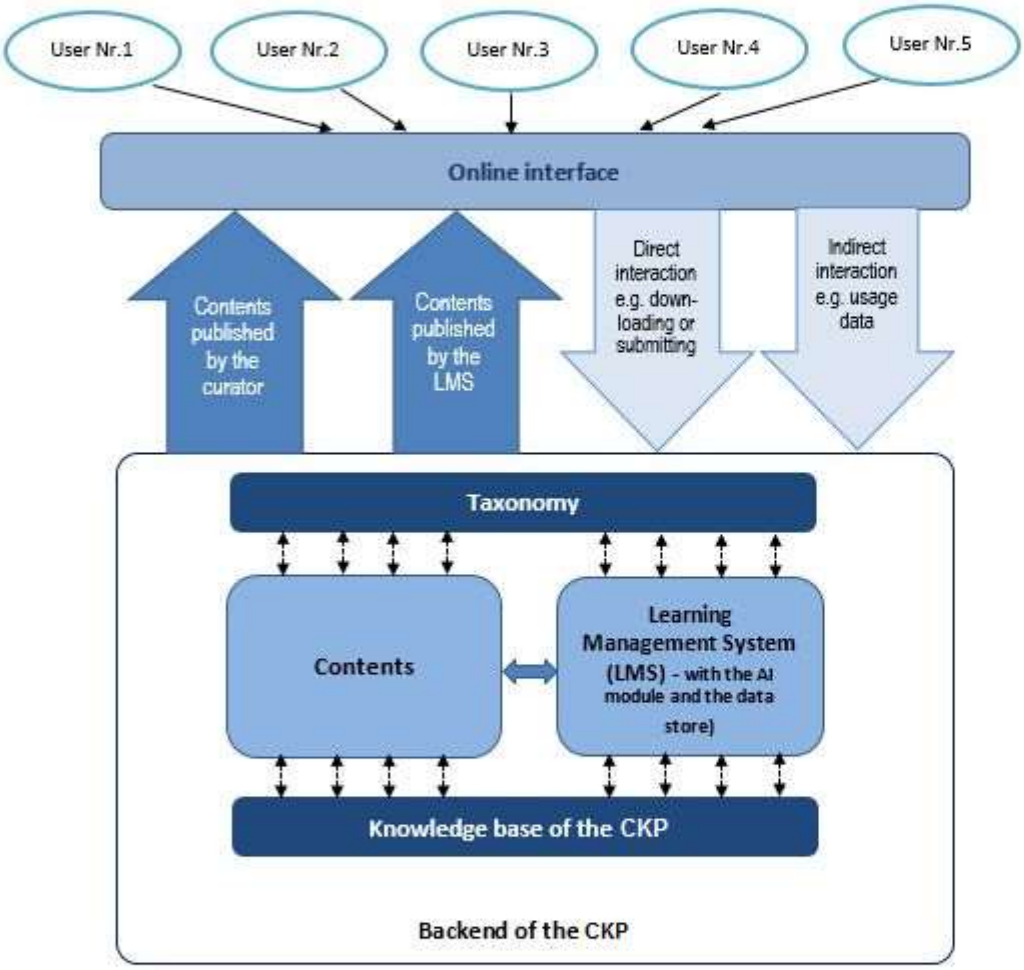

Image source: own research result

Figure 3.4.- Mashup architecture of the CKP

The purpose of these patterns is to show the learning routes of the individuals as cases and rules for the Knowledge Representation (KR). Actually, the learning route is outlined by the following specific links and the logs of their usage inserted to the database. The logs are generated by the access of these special links which are not only connections but their direction from a starting unit to an end unit and backwards is important. Users can select from different contents to use with the help of a dialogue interface. Each usage of a given content is written to the log and consists of at least the time stamp of the usage with the duration of the access, the identification of the user and the direction of the link. Based on these data a report can be generated as rules of the user's interactions. After a certain number of interactions and an amount of time spent with them, an assessment point can be embedded in order to evaluate the user's level of understanding. The gathered data can be systematized relating to the users and this will be the feedback to the content curator about the necessity and the usefulness of each content unit. If the assessment can be performed without one or the other content unit then that element may be unnecessary for understanding but when the user gets stuck with an element then there may be a need for help in it. The traces of learning routes can be captured by using the extract data allocated to the links successively and used by a user during a database access. The logs will be the base of monitoring and creating the association of the user’s own learning manner and the Knowledge-based System helps to recognize the common behavioral patterns. According to the object of the method, this Knowledge Representation is condensed from the whole process and it can be shared among the individual users in order to encourage the collaboration. “The process of KR is that when we create new symbols from the previous ones during the whole thinking process. Everything, between the input and output, belongs to the examination of thinking. The transformation of symbols always happens based on some sort of rules. According to Boole’s concept every knowing is derived from logical and arithmetical operations” (Velencei, Szoboszlai, Baracskai, 2014). That is the reason why the Knowledge-based System cannot be considered only a software or a representation of knowledge but it meets the requirements of both at the same time (see Fig. 3.5.).

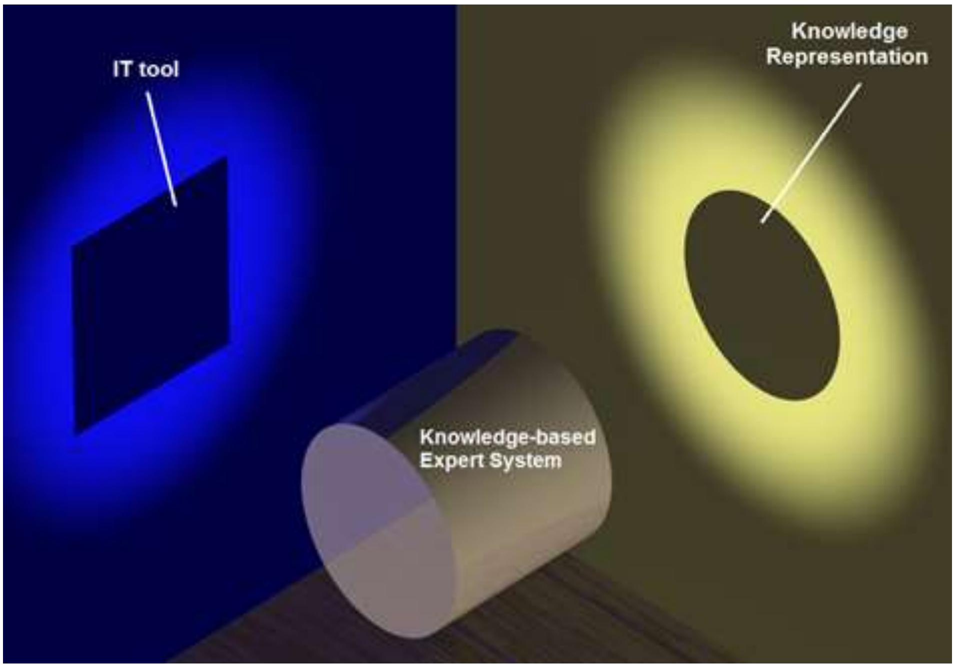

Image source: own research result

Figure 3.5. - Perspectives of the Knowledge-based Expert Systems

As we can read in Wagner's summarizing study (2017) although there are different KR techniques, it seems that logical rules have still been dominant over the last thirty years. As far as the process of KR is concerned, it has definitely changed and some new methodology has been introduced (Cairó & Guardati 2012)(Tsui, Wang & Lee 2014). Symbols in this interpretation are soft data which come from the users' behavior: how they use the contents, how they put them into their context, how they interact with each other beyond notions and disciplines. Soft data must be transformed to hard data in order to implement them into the logical operations. Actually Knowledge-Based Systems are usually used to evaluate decision alternatives, those are called 'cases' therefore these systems belong to the Decision Support Systems as we can read it in Zaraté's reviewer study (2016). In case of the CKP, the contents are offered as decision alternatives, these are the cases which should be evaluated. The evaluation of the contents as 'cases' happens by reasoning, so the recommended contents are the results of case-based reasoning. In order to get better quality or more relevant recommendations for the contents, the system needs to learn. To achieve this, a new method, the case-based rule reasoning can be applied as a reduction of a decision model. During the knowledge engineering process, when the system automatically accepts the case-based graphs of the content evaluations, a new rule-based knowledge base can be created, which contains only the informative attributes of the users' learning route. This reasoning uses rules but they are induced from the set of cases, thus this type of reasoning is called case-based rule reasoning. As the new knowledge base is generated automatically by reducing an existing model, it is also called reduction as we can read in the documentation of an expert system with this unique feature (Baracskai, Velencei & Dörfler 2005).

3.4. Conclusion

Although, the system discussed in this paper is just a concept, it is conforms to the ISO 30401 standard because it is suitable for knowledge transformation by human interaction, externalization (recording, documentation or coding of knowledge), curation and combination (synthesis, formalization, structuring or classification of codified knowledge), accessibility and internalization (for easy access and understanding) (Maximo et al. 2020).

The development of a CKP as suggested in this article intends to get different particular achievements in the field of Knowledge Collaboration and Knowledge Management Systems. One of these is an attempt to develop a new Knowledge Representation technique by integrating symbolic logic and artificial neural networks. The other one is to create a new machine learning algorithm which enables the system to convert results of case-based reasoning into a new rule-based knowledge base and that could be the core of a new experience mining method. By this, members of the knowledge community can learn from other's knowledge or experience and it could shift the personal knowledge creation to a more collaborative model within the informal organizational learning. In addition to the goals mentioned above, it would also make contributions to the fields of cognitive sciences, as a new model of collaborative situated online learning which would be different from the cited examples in the Literature overview.

3.5. Limitation

Although this is a conceptual paper, we assume that there are some limitations without which the described collaborative knowledge platform cannot be developed. The first one is that unique method which is able to draw up the learning route. In the lack of the implicated case-based rule reasoning method, the system may be similar to the known ones which collect only network usage data in order to access to various identifiable information sources in the network. For this purpose, those continuously monitor and analyze the usage information (e.g.: access of different contents and the time spent there). The learning route is a form of knowledge representation instead of simple interest. The limitation of the method stems from the general characteristics of the usage of the applications for example we cannot always be sure that the logs reflect the real activity of the user, as the duration can also be distorted by simply leaving the application open or the user can browse randomly without a real learning purpose. In connection with the method, as a second limitation, there is a need for the core element that is able to reduce the decision alternatives to the most informative ones. Finally, as a third limitation, the implementation requires a dedicated, engaged and qualified content curator to manage the knowledge collaboration.

4. R&D project evaluation at a university with Knowledge Acquisition

Working paper:

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ABSTRACT

Significant research on R&D project evaluation methods is feasible when we have clear data and conditions for measurement. In university projects it is unwise to use directly the reference points and practices of industrial or independent labs. As a result, the method and the model introduced in this paper are adapted to find the most informative success factors for engineering R&D projects when the non-professional project manager's experience is the primary source of data. The model was developed using Knowledge Acquisition (KA) while 21 projects within the same domain were recorded in the knowledge-base by semi-structured interviews with experienced project managers during a fine-tuning process. The contribution of this paper is the logical rules and the attributes by which we can understand the project managers' mindset in R&D projects of a higher education institutions. The paper includes an evaluation of the projects as a case study.

Keywords: *university laboratories, R&D projects, project evaluation, Knowledge Acquisition*

4.1. Introduction

Currently most methods and tools developed in the field of project management, more precisely in the field of project evaluation, are applicable in cases where enough depth and systematized data is available. R&D projects in industrial environments typically produce a large amount of accessible data that can be used for project evaluation but this is not typical in a university project environment. The theoretical lens of this research focuses on cases where the project evaluation process can only rely on data directly from the experienced decision maker and the project managers as a body of their knowledge. In this paper we would like to present the path that leads to the results of an R&D project evaluation in a university laboratory when necessary data is formed during the process with the help of the project managers. This article describes the way in which data was gathered, how the model was developed and how the resulting rules can be applied as a starting point for project planning. Knowing the most informative rules, we examine the difference between the approaches of the operation of a university lab and the professional development of industry. In order to explain the main points of contrast, we have to understand the most important expectations of the participants of the projects, and how these expectations lead to the relationship between the two parts of these projects: research and development. R&D projects should essentially aim to manage the manifestation of continuous change and novelty in turbulent times, and as such, also aim to manage the unexpected. As Weick says in this regard: “If you want to manage the unexpected, you have to understand, first, how expectations work and, second, how to engage them mindfully...” (Weick, 2007 p. 23) As these projects were semi-structured or ill-structured processes with regards to their problem definition, it is interesting to understand the expectations from the perspective of the participants. An expectation is one of the ways of looking at the optimal ambition problem if we accept that “Individuals and organizations form aspirations, goals, targets, or ambitions for achievement. These ambitions are usually assumed to be connected to outcomes in at least two ways: they affect search (either directly or through some variable like motivation) and thereby performance; they affect (jointly with performance) satisfaction” (March and Simon, 1958, p. 423). In this research evaluation of finished R&D projects occurred by forming these expectations as attributes from a ‘scale’ aspect instead of a detailed numerical data analysis.

Although this research is project management related, in order to fill the research gap, according to the approach suggested in Hanisch and Wald’s study (2011) the authors endeavor to extend the dimension towards the field of decision support and borrow some terms from there. When we discuss the difficulties of knowledge capitalization processes at the organizational level, we actually have to solve a) the problem of intangibility and codification of knowledge in order to reuse it (Coners and Matthies 2018) b) how to validate the contribution of each interviewed project managers. Knowledge Acquisition (KA) can be a solution to question a) and Knowledge Engineering (KE) and Knowledge-based Systems (KBSs) for b). According to this, the presented research was a KA process when project managers needed to rely on their previously gained knowledge elements that did not exist in written form. In order to systematize these knowledge elements into a consistent knowledge-base and to build a model from them, a Knowledge Engineering process was required which was supported by a Knowledge-Based System as a tool. The term refers to using software tools to utilize knowledge-bases and which are expected to perform at the level of a human expert. During this process, according to Chua, “a knowledge engineer must represent acquired knowledge in such a way that a human can understand it and a computer system can process it.” (Chua et al., 2012 p. 304) In this research the authors use the Doctus Knowledge-Based System, which is for systematizing prior knowledge and experience and is able to build models for different scenarios. The knowledge-base is built from the evaluated projects as cases, and the authors tried to obtain findings by recognizing the most informative attributes via case-based reasoning and aimed to capture the differences between industrial development projects and university R&D projects.

The question of the study is 'what are the most informative attributes that affect the success of university R&D projects? As a result, a model is provided about the most informative attributes and the logical rules between them.

The paper is structured as follows. First we consider the relevant literature based on the topics of R&D projects in university labs focusing on the researcher attitude and motivations of academics, as well as project evaluation methods concentrating on success factors, and finally the KA trends and techniques. After this we clarify the methods and describe how this research was conducted and how data was collected. We discuss the main points of the fine-tuning process of knowledge engineering and our findings from the 21 cases.

Finally, we draw the conclusion from our results and define our research limitations as well as future research perspectives. We demonstrate how this study contributes to project management with a technique that enables project organizations to evaluate R&D projects based on the knowledge and experience of the project manager.

4.2. Literature review

Since our study is qualitative research, according to Müller-Bloch and Kranz's framework for identifying research gaps in qualitative literature reviews (Müller-Bloch and Kranz, 2015), we first determined the review scope around the following four key topics:

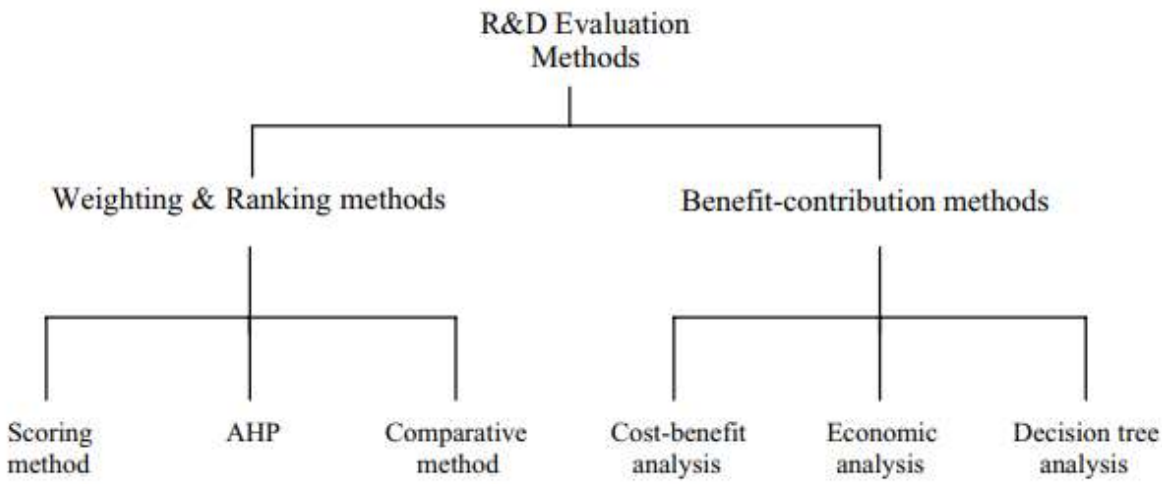
- R&D projects and university labs
- Project evaluation methods
- Knowledge Acquisition
- Academic communities

R&D projects

The majority of the studies available concern the operation and evaluation of industrial R&D projects from a variety of aspects (e.g., Khedhaouria et al., 2017, Faccin and Balestrin, 2018, Rogers et al., 2017) but we can find far fewer findings about similar projects in universities. There are some recent studies attempting to analyze the importance and execution of projects in universities (Stukalina, 2016) and the emerging role of universities in developing regional entrepreneurial ecosystems by R&D activities (Fuster et al., 2019), and there is evidence for a very high impact on product innovation by collaboration with universities (Un et al. 2010). Some of them examine these activities from the aspect of knowledge transfer (Bozeman et al., 2013)(Bansal et al., 2012). Further studies focus on value co-creation by university and industry (Canhoto et al., 2016) or collaboration between them (Szűcs, 2018). Others developed hybrid management approaches for university-industry collaboration (Fernandes et al., 2018). Some of them emphasize the challenges of university-industry collaboration in R&D activities and try to bring recommender systems as a solution (Wang et al., 2017)(Yumusak et al., 2015). Probably Mahmood's study (Mahmood et al., 2014) examined academic research projects from a very similar perspective to our research problem, but, since his research was conducted with content analysis, the results point out the critical success factors of the projects without the logical relationships between them.

Project evaluation

In the last few decades, several studies have been published about R&D evaluation methods. Some of them provide comparative analysis of the methods, such as Poh's study (Poh et al., 2002), which helped us identify our research method in a new system. According to Poh's classification (Poh et al., 2002), all methods of R&D evaluation can be classified into two main categories as either weighting and ranking methods or benefit-contribution methods, as shown in Figure 4.1.



Source: Poh, K. L., Ang, B. W., & Bai, F. (2001). A comparative analysis of R&D project evaluation methods. R&D Management

Figure 4.1. - R&D evaluation methods

During the research conducted for this paper, a decision support system was used and a case-based graph was produced as a decision tree, which means our method belongs to the benefit-contribution branch, and within that to the decision tree analysis inasmuch as case-based reasoning was applied.

Others offer decision methods for collaborative R&D project selection based on competitiveness and collaboration performances (Feng et al., 2011), focusing on mathematical decision models and their applications (Tian et al., 2005). Further studies recommend different methods based on data envelopment analysis (Eilat et al., 2008)(Karasakal and Aker, 2016)(Ghapanchi et al., 2012) or evaluate the projects based on critical success factors via the artificial neural network model (Constantino, 2015) or based on systems approach (Anbari, 1985). Some more recent studies presented data-driven evidential reasoning rules (Liu et al., 2019) for R&D project selection problems and decision-making (Thirathon et al. 2018), although, data science analyses faces challenges (Saltz et al., 2020). Some frequently cited studies focus on project success criteria such as Westerveld's, which linked success criteria and critical success factors (Westerveld, 2003) or Müller and Turner's, which examines the influence of project managers on success criteria (Müller and Turner, 2007).

Knowledge Acquisition and Knowledge Engineering

As referred to in the introduction, Knowledge Acquisition (KA) is a widely known and introduced term borrowed from the field of decision support systems. This is an adequate method for building knowledge-bases from experts' knowledge and experience. The proposed KA techniques were presented by Boose three decades ago (Boose, 1989). Some studies examined the trends of this long period: Wagner's review paper is based on Boose's often cited study (Wagner, 2017). Kidd's book (Kidd, 2012) and Zaraté's study (Zaraté and Liu, 2016) give some useful suggestions in the field of KA and decision support systems. Their findings meet with the approach of our research. Studer's study (Studer et al., 1998) presents the relationship between KE and the types of Knowledge-based Systems like the one used in our research, and gives an overview of the development of the field of Knowledge Engineering. That paper "put the emphasis on the paradigm shift from the so-called transfer approach to the so-called modeling approach. This paradigm shift is sometimes also considered as the transfer from first generation expert systems to second generation expert systems." We can find other research which tries to use methods and systems for reasoning from unstructured and narrated information (Wang et al., 2011)(Lämsä and Sintonen, 2006).

Understanding Academic Community

Project evaluation process presented in this study happened in a university within an academic community. The theoretical lens we apply is based on a new conceptual framework of academic community, and its place in the larger context of the economy. In order to understand these communities, we have to begin with the observation as to why our research question is only valid in a specific environment. The theoretical lens we apply is based on a new conceptual framework of the Academic Community, and its place in the larger context of the economy. While it seems self-evident that the engagement and passion of project managers is a key success criteria of any project, it seems especially indicative of the probable success of reversed D&R projects of academic labs. Furthermore, understanding the different development paths of these project managers (Savelsbergh et al., 2016) can help us answer the question of a study very much relevant to our own: Do all project managers have the same perspective on project management (Andersen, 2016)? In order to fruitfully compare the R&D projects of a profit-oriented organization with the D&R projects of a university lab, we have to understand the Homo Economicus habitus and the fields (Bourdieu, 1988) of academic project orientation as an opposite to the key factors of the design of a company project manager's career path (Hölzle, 2010).

The above criteria and goals help us discern the environment within which our research question is valid; we are honing in on a problem space that tries to intersect and harmonize industrial R&D, classical Homo Academicus habitus and Academic Capitalism (Fig. 4.2).

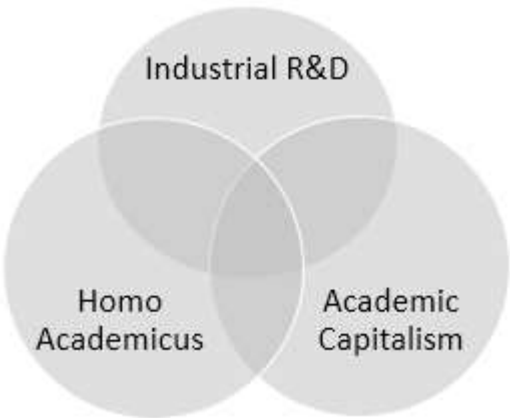


Image source: own research result

Figure 4.2. - Intersection of the research problem space

Understanding the above intersection, and with the introduction of the ideas of *habitus* and *field*, we have to expand our lens to include borrowings from another discipline. A brief and selective introduction to Bourdieu's concepts of *habitus* and *fields* (Bourdieu, 1988) can be focused on Homo Academicus, whereby academia is shown to be not just a realm of dialogue and debate, but also a sphere of power in which reputations and careers are made, defended and destroyed. In the intersection with Industrial R&D, the industrial environment has generally accepted the *field* and *habitus* of academia, but has always taken a careful approach to the academic community as a whole. There seems to be a preference for carefully selected individuals rather than entire labs. Richard Münch' study (Münch, 2013), entitled 'Academic Capitalism: Universities in the Global Struggle for Excellence' offers a new concept for universities as follows: "Academic capitalism is a unique hybrid that unites the scientific search for truth and the economic maximization of profits." Jessop in an earlier study (Jessop, 2017) presents three experiments: rethinking the rise of academic capitalism; rethinking entrepreneurial universities; rethinking the varieties of academic capitalism. He collects and divides conceptual views according to these experiments and concludes with the types of capitalism that affect science in different ways. But Jessop in a recent study (Jessop, 2018) highlights the dark side of academic capitalism.

The phenomenon of "Academic Capitalism" and the stable role of "Homo Academicus" are elements of the milieu where industrial development exists. The origins of this can be found in experimental and basic research started from results of engineering development. Developing a product or procedure means a real challenge for Homo Academicus. They go through a different process, since they come up with the novelty first and then think about how to distribute it.

4.3. Methodology

Data collection and Knowledge Acquisition

For the sake of building a knowledge-base from the experience of the project managers, we found it adequate to apply Knowledge Acquisition (KA) for data collection. According to the classical distinctions of qualitative data collection methods, our research is based on data from semi-structured, in-depth, individual interviews as a way of KA. This interview form ensures a greatly expanded process of data collection and a depth of gathered information "which encourages the interviewee to share rich descriptions of phenomena while leaving the interpretation or analysis to the investigators," as is published in the seminal study of DiCicco-Bloom and Crabtree (2006). This data collection method is commonly used as a part of participatory action research when "people are engaged in examining their knowledge (understandings, skills, and values) and interpretive categories (the ways in which they interpret themselves and their action in the social and material world)" (Kemmis and McTaggart, 2005). In light of this, the occasions when we talked to the project managers were not only interviews; Knowledge Engineering happened simultaneously. The goal of a KA process is to draw as much knowledge from the interviewees as possible. The intention of knowledge engineering is to see the big picture as a system while the used terms should have the same connotation for the knowledge engineer as for the interviewees. As we applied an approach in order to understand the conceptual framework, we invoked the knowledge of several disciplines such as behavioral economics, knowledge management, project management, decision support and other social studies.

Based on de Kock (2003), we defined the significant stages Knowledge Engineering has, as presented in Figure 4.3:

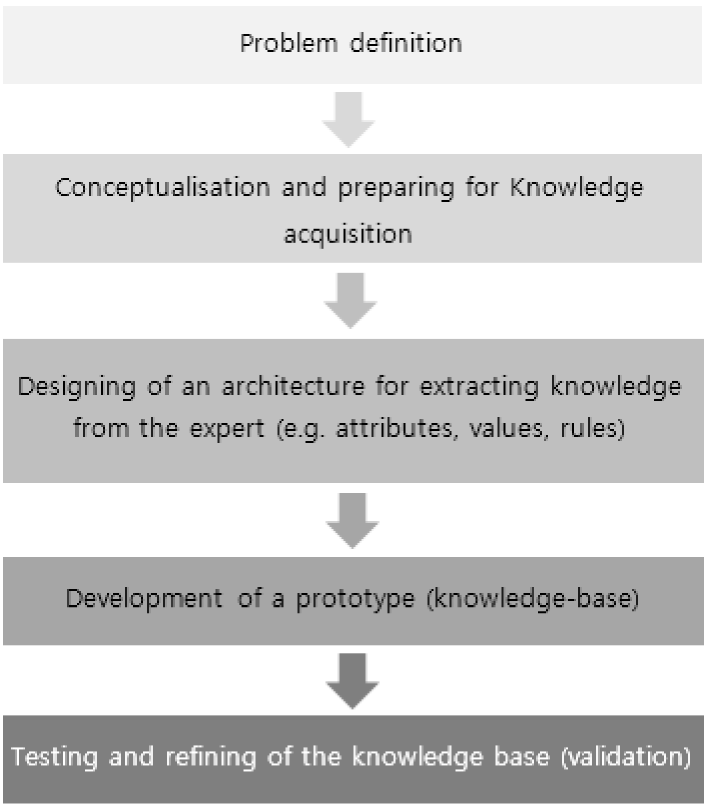


Figure 4.3. - Stages of Knowledge Engineering

In this current data collection process we followed these steps:

- <u>Selection of the interviewees:</u> First, the university was selected on the basis of a sufficient number of relevant R&D engineering projects. Sufficient number means that at least 20-30 relevant projects should be in the same domain to build a knowledge-base from them. After this we identified the most active and most experienced project managers as interviewees with the help of the project portfolio manager. He suggested those 7-9 interviewees who had finished at least 3 to 5 R&D projects, each in the university as academic people and professional project managers in one. Women and men were mixed, there was no age restriction. Among them were PhD students in the research phase, researchers or teachers at the university. They managed their projects as a part-time job with 4-6 team members.

- Initial set of attributes with values: Generally, the systematized evaluation of cases requires the obtaining of at least 15-20 relevant attributes as a set of well-ordered preferences, and at least 3-4 different values must be assigned to each. In a case where there are too few attributes in the knowledge-base, we cannot state that the system of expectations is sufficiently sophisticated, and at the same time there is a chance that the individual's cognitive biases can significantly impact the outcome of the process. In our research, the project portfolio manager defined the initial set of attributes to the knowledge-base. This means that he or she narrated the first two stories while articulating those 16 criteria and related 3-4 values by which a typical R&D project in the university can be evaluated. As an example, he or she provided the first definition and values of project results as follows. Result of the projects can be described by the following values: "according to the agreement" as a value was used for the successful project, "financially failed" as a value meant that although the customer was satisfied with the project completion, it was over-worked. This does not strictly mean cost overrun because in a university environment cost of R&D is different from industry. "Over time" meant that the project was delayed, and there were some projects that were started with the research phase and based on the results of this the planned project officially "was not started". These initial sets of attributes and related values were the starting point for the fine-tuning process with the project managers.

The interviews: This part of the work was a very interesting fine-tuning process, during which the system of the initial set of expectations was refined step by step with each of the 8 interviews. Our interviews consisted of two main parts. First we asked the interviewees to choose 2-3 projects he or she was in charge of. There was no restriction as to the size of the projects or the subject. The projects had to be based on applied R&D activities, which are strongly related to the manufacturing sector and dominantly in the automotive industry. Inclusion criteria focused on the outcomes of the projects. These should be between two ranges in order to keep focus on applied researches. The outcome should be the development of a procedure or a product, or any other manufacturing activity. A significant requirement was the difference in project result. There had to be successful and unsuccessful projects in the sampling to recognize what causes the difference of the result. In the first part of the interviews we asked the interviewees to talk about the project in general. As was published in James March's frequently cited study on organizational decision making, people can remember and recall colorful stories and information more easily than the data of statistics (March, 1991). This might well explain the importance of story-telling and social narratives in knowledge acquisition processes.

In the second part of the interviews we asked them structured questions about the chosen projects with the attributes and values from the knowledge base. During this we incrementally tested the initial set of attributes and values in each consecutive occasion from the aspect of whether they were really familiar to the current interviewee. In cases where the interviewee's answer did not connect to any value of a given attribute, the answer was added as an extra value to that attribute. This part of our research had two objectives. Firstly, to avoid a situation where interviewees mechanically use the sentences and terms given to them instead of their own. Secondly, to ensure that all of them keep the essence of the same terminology. In order to achieve these, the interviews were coordinated by a knowledge engineer.

As a result, our interviews were semi-directed story-telling processes about the projects, using the same questions in each interview. These stories helped us understand the circumstances among which the projects and project managers exist. We tried to capture the mindset of the participants that determined their thinking as Homo Academicus and Professional Developer in one. This understanding is a typical and crucial endeavor of the Knowledge Acquisition process, since it is not about the expert, in this case the project manager, directly talking common sense. Instead, it is about finding the most adequate system of preference orderings the interviewee can think of.

The interaction between the expert (project manager) and the knowledge engineer is demonstrated in Figure 4.4.

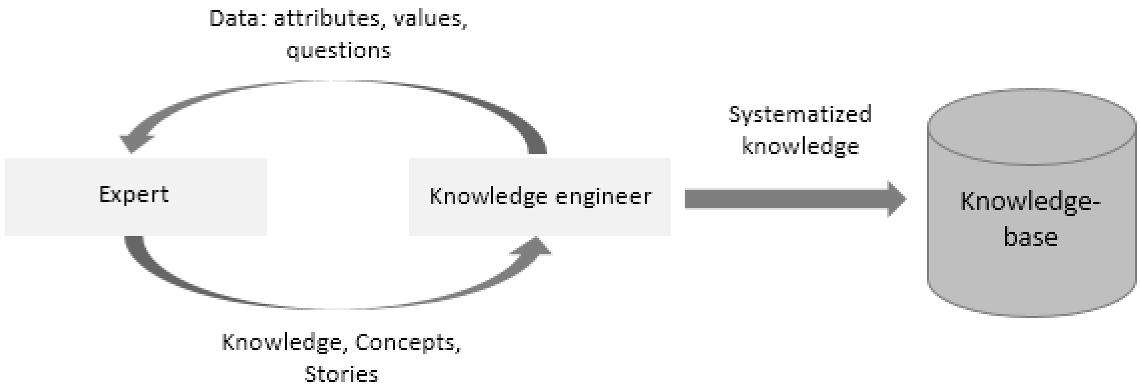


Figure 4.4. - Process of Knowledge acquisition

The Knowledge-base

As illustrated in Figure 4.5., 16 attributes were collected in the knowledge-base, some of them in connection with the human relationships within the projects; for example, “Relationship between the project manager and customer”, and others about general characteristics, like “aim of the project”, for instance. We have to note that no attributes are included among the expectations that could be derived from financial data.

Name
RESULT
project manager's experience in coordination
project manager's character
project manager's experience in the domain/topic
constitution of the developer team
aim of the project
the team leader's relationship to the topic
the team leader's capacity
project manager - team leader communication
relationship between project manager and customer
customer
problem definition
source of the idea
prior knowledge
timeframe
project manager change

Image source: own research result ű

Figure 4.5. - Attributes in the knowledge-base

Two values of the (project) RESULT refer to financial information. The first value is “according to the agreement” which means that the project was closed in time and with the original budget and the second is “financial failed” which means that more resources were included in the project than it was planned. As is mentioned above these values are used in abstract form, without numerical facts supported by financial reports. In accordance with the KA method we assume that experienced project managers, like our interviewees, are able to evaluate the success of their completed projects based on the patterns of thoughts as cognitive schemata in their mind. All these aspects are therefore the kind of 'soft' information that can be acquired only from the project managers' minds and nowhere else.

It was also interesting to observe the evolution of the final set of attributes; some attributes were removed from the knowledge base due to the fact that after a few interviews they turned out to be irrelevant to the evaluation, while others were inserted. For example, originally, there were two attributes named "Project manager's character" and another as the "Professional leader's relationship to topic". However, both of them had a slightly different value and meaning, and, as it became clear that in most cases the professional leader and the project manager were the same person, the second attribute seemed unnecessary.

Conversely, at the start, "Project manager change" had not been among the criteria, but, during the second interview, a detailed story was told about a completely transformed project during which the project manager was changed for certain reasons. At this point we had to insert this new attribute with three values, and, furthermore, the first attribute, listed above as (project) "RESULT", received a new possible value called "Transformed". This value is used for projects prolonged by legal action, or where conditions of the related contract were significantly modified by the parties. All in all, this case is one of the authoritative and adequate examples of why the role of knowledge engineer is decisive, and why it is important to be competent in the field in which the process is supported. The interviewee started the story of the project from the point of view of it being a failed project. But as the story began to unfold, it turned out that it just seemed to be his own personal perception, since the project was not realized as it had originally been planned; the scope was significantly changed, the time frame was extended to an indefinite duration, and some key team members were changed including the project manager. The parties of the contract, however, (including the customer) never declared it a failed project. The project manager's personal dissatisfaction caused his cognitive bias in the judgment of the result. Finally, however, after we discussed the issue from a broader perspective, he accepted the opinion that it was a "transformed" project instead of a "failed" one.

Each of the attributes had been assigned 3 or 4 values, in one case 5 values, as is illustrated in Table 1. During the fine-tuning process, some values had to be replaced because their original meaning proved too pejorative. For example, the first value of the "project manager's character" originally was "careerist" but it seemed too negative for the interviewees and they were reluctant to choose it, so later it was replaced with "career-driven", which has a slightly more positive connotation, since it refers to someone who is very self-conscious in their career. Immediately after we replaced it, some interviewees were open to choosing it. There were some particularly interesting values. For instance, values of "Prior knowledge" were articulated as "we have experience", which means that objectives of the project were known to the participants at the start and they just had to adapt to a new project. The second value was "We have knowledge but no experience", which means theoretical knowledge without practice and justification. The third one was "We know who to ask", which means only the knowledge of the problem space, and it was the case when members of the project team knew who the most influential researchers in the field were, and whose results or studies had to be read in order to solve the problem. And finally, a value was defined for a situation when there is no prior knowledge in fact as "there is no one to ask". After creating the initial attribute set and its values, the interviewees selected the relevant values for each project, if it was already there in the correct form. When we found that none of the available values were suitable for that particular situation, we rearranged the current value set somewhat to insert the new one. The outcome of this process resulted in the knowledge base from which the case-based reasoning would start. Cases in our knowledge-base are the projects and the evaluation of cases is referred to as reasoning.

Name of attribute	Value 1	Value 2	Value 3	Value 4	Value5
RESULT	according to the agreement	financial failed	delayed	it didn't even started	transformed
Project manager's experience in coordination	beginner	advanced	master	nothing	
Project manager's character	career-driven	passionate	does the job	not in good mood	
Project manager's experience	beginner	intermediate	advanced	master	
Project team formation	external workers	internal workers	both		
Goal of the project	technological adaptation	development	testing	problem-solving	
The team leader's relationship to the topic	forced to commit	accepted	enthusiastic		
The team leader's capacity	free	average	overwhelmed		
Project manager-team leader communication	convincing	senseless	irrelevant		
Relationship between PM and customer	frequent knowledge sharing	official	stormy		
Customer	one	more	transferable anywhere		
Problem definition	well-structured	semi-structured	pseudo	changed the scope	
Source of the idea	manufacturing	developers of the customer	outsider	researcher	
Prior knowledge	we have experience	we have knowledge but no experience	we know who to ask	there is no one to ask	
Timeframe	irreal	fits to the resources	with resource expansion		
PM was changed	no	after partial results	because of incompetence		

Table 4.3 Final attributes with their values in the knowledge-base

4.4. Analysis and results

To obtain the most informative attributes that are the key success factors of the examined projects based on the knowledge-bases presented, we need to evaluate the cases by case-based rule reasoning or we can call it reductive reasoning (Baracskai et al., 2005), since it is a reduction of the model. It happened with "if…then" logical rules applied by the Knowledge-based System (KBS). The KBS we applied uses the ID3 algorithm that builds an increasingly complex decision tree (hypothesis) from the available data (Quinlan, 1986). The tree is essentially a Case-Based Graph created via the formula of entropy.

Based on the reasoning described in brief above, we obtain a case-based graph and at the top of the graph the most informative attribute is shown.

Our final case-based graph after the reductive reasoning is illustrated in Figure 4.6.

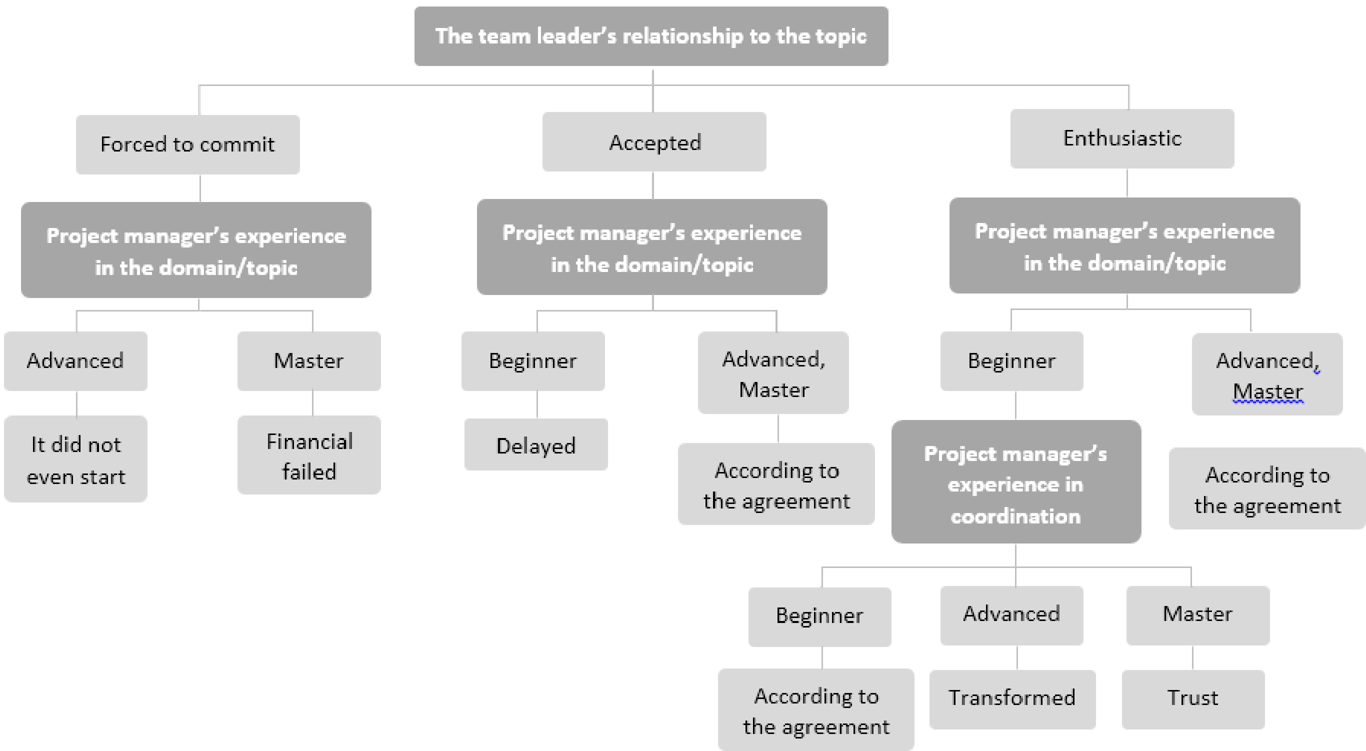


Image source: own research result

Figure 4.6. - Case-based graph of the knowledge-base after reasoning

If we sort the attributes by informativity, we get the following table (Table 4.4.)

Attribute	Informativity
the team leader's relationship to the topic	0.3439
project manager's experience in the domain/topic	0.3196
project manager's character	0.2596
problem definition	0.2355
prior knowledge	0.2299
project manager - team leader communication (2)	0.2170
timeframe	0.2118
source of the idea	0.2025
project manager's experience in coordination	0.1973
aim of the project	0.1841
project manager change	0.1814
customer	0.1671
relationship between project manager and customer	0.1592
the team leader's capacity	0.1482
constitution of the developer team	0.0708

Table 4.4. - Informativity of the attributes

We can see that the most informative attribute is “the team leader’s relationship to the topic”, both at the top of the graph and at the top of the list. Based on the result of the evaluation we can articulate some further informative rules as well:

- if “Project manager’s experience in the domain/topic” was “master”-level, but “the team leader’s relationship to the topic” was “forced to commit”, then the result of the project was “financial failed”;
- if “ Project manager’s experience in the domain/topic” was “master” or “advanced”-level and “the team leader’s relationship to the topic” was “accepted”, then the result of the project was “according to the agreement” ;
- and it is very interesting to note that if “Project manager’s experience in the domain/topic” was “beginner”-level and his or her “experience in coordination” was also “beginner”-level but “the team leader’s relationship to the topic” was “enthusiastic” the result of the project was “according to the agreement”.

If we apply the principle of Occam’s razor (Elliott, 1994), which says "simpler solutions are more likely to be correct than complex ones", we can get a simple result according to Figure 4.7 which presents the three most relevant criteria from the aspect of the project result. The results of our research were presented at a workshop where the interviewed project managers participated.

Image source: own research result

Figure 4.7. - The most informative attributes

The most important validation of the results was that the participants in the research recognized their own mindset.

4.5. Discussion of the findings

The main objective of this research was to examine the most informative aspirations in R&D projects of university labs and the logical relationship between them. Since there was not enough hard data from project management support systems or management information systems, we applied a method borrowed from decision support, namely Knowledge Acquisition. The results can be discussed as follows.

Theoretical implications for academic R&D projects

We found that the project manager's experience and the team leader's relationship to the topic are the criteria which have the most significant impact on the success of the investigated projects. This means that, although there is evidence for significant impact of many other factors on the project success, such as the impact of emotional, intellectual and managerial leadership competences (Müller et al., 2012)(Diskiene et al., 2019), as well as job satisfaction and trust (Rezvani et al., 2016) and even different management perspectives, (Andersen, 2016) the results of our study provide evidence partly for other factors. According to the found rules, in order to successfully execute an R&D project in an academic environment, the team leader must be "enthusiastic" about the topic and not be forced to commit to it. Academic project managers seek challenging projects from the aspect of their research field. We found that in cases when the project manager or the team leader started a project without this enthusiasm, but they wanted to advance in the university hierarchy

(Bordieu, 1988) or to gain the satisfaction of those who are important to their scientific advancement, then the project was usually financially failed. That means the customer accepted the completion but more effort was involved than originally planned. The higher complexity of searching for a solution in R&D projects with fixed price and time contracts increase the risk of cost overrun. These findings point out the main differences between a professional project manager and the Homo Academicus. It seems in many cases academics see projects as a real mission to improve their discipline. Based on the recorded project stories we found that this sense of mission can drive the project forward, but it can also be counterproductive by overriding the professional management attitude. Because of this, in most of the examined cases, the two parts of the project, research and development, are started in reverse. This happens because, in order to solve the problem, development happens first, and only after that, due to the scientific curiosity and commitment to the topic, is an academic research process started as an extension of the original project.

Managerial implications for project evaluation

The study offers a method for situations when there is not enough hard data to evaluate projects but experienced project managers are available to share their knowledge through interviews. This method can also be applied as an additional one within the current project closing and evaluation procedure in cases when there is abundant data from project management systems, but the organization can also facilitate knowledge creation based on the projects.

We assume that our study can open the door for the wider use of KA in project evaluation. This approach can be used in any kind of project evaluation when knowledge creation is required based on results of the project organization. According to the feedback from our interviewees, knowledge creation had happened when they validated the model together. It seems that in the validation workshop, the model and the knowledge base incorporated with their prior common knowledge about their projects. The reason for this being, in reference to Weick's novel approach to a redefinition of learning, "individual learning occurs when people give a different response to the same stimulus, but organizational learning occurs when groups of people give the same response to different stimuli" (Weick, 1991, p. 121). Savelsbergh's study (Savelsbergh et al. 2016) points out that most learning experiences of project managers occur more or less accidentally on the job. We hope that our presented method can be a way to a more directed learning instead of accidental, or even to a knowledge synergy (Skačkauskienė et al., 2017). In our study, knowledge creation focused on the individuals' role in the projects and the reversed R&D projects that operate specifically in universities.

4.6. Conclusion

The goal of this research was to examine how R&D projects in a university could become more successful, and the outcomes can be used as a promising starting point for future strategies of project planning on a wider scale. Organizational behavior, and within that the importance of experience and passion, are often not properly handled in project management, but our results show that these may be even the most relevant criteria for academics. The findings allow us to conclude that R&D projects in universities operate vice versa in many cases as D&R.

Acknowledgement

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5. IF…THEN SCENARIOS: SMART DECISIONS AT SMEs

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Abstract

In the last few years the behavioural economics has been closing up to the traditional economics which must count and measure everything. We can observe this phenomenon in the field of the business decisions where the bounded rationality was recognized by Herbert Simon (1982). Nowadays Simon's thesis has just been turning into smart decisions. What makes a business decision "smart" and whether we can support this kind of decisions efficiently at SMEs or not?

The actuality of these questions comes from the fact that we can recognize a paradigm shift much less in the field of business making than in the info-communication in the last few decades. Experts are convinced that in the field of decision supporting there is an upcoming paradigm shift whose main point is that the models, based on the allocation of scarcity resources, have lost their relevance in the time of abundance, more precisely they have over-swelled their domain (Velencei, Baracskai, 2016). So studies and researches show that in the time of abundance the keys to a smarter complex decision making are the behavioural patterns which can be recognized by for example knowledge-based expert systems. According to Daniel Kahneman, as one of the most respected behavioural economists, the model of intuitive decision-making, as pattern recognition, is a further developed form of Herbert Simon's thesis (Kahneman, 2011).

C.K. Prahalad and Gary Hamel ask the question in the prestigious Strategic Management Journal (Prahalad, Hamel, 1994) "Why search for a new paradigm?" Actually why is a new management paradigm necessary? Probably we will see the innovations in another way through new eyes and perhaps we can support the intuitive decisions not only at large

enterprises but also at small and medium ones by these knowledge-bases and patterns in them.

Keywords: behavioural economics, decision support, smart decisions, knowledge-based systems, expert systems, SMEs,

5.1. Background knowledge

It is a widely known fact that SMEs do not often use business consultancy in their operation (Kaufmann and Tödtling 2002) (Ates, Garrengo, Cocca & Bititci 2013) and it is particularly true for the field of supporting of complex decisions. In most of the cases they do not even by a special software for it. Executives of these smaller companies, in complex decision making situations, decide typically alone, intuitively and in several cases very quickly. That is less well known, actually they often use very few data, rely on their own experience in these processes, and since they are mostly sensitive to the costs thus the financial aspects are overemphasized in their decisions. The prevalence of these cognitive biases during the decision making processes has been demonstrated in several studies. The thesis of bounded rationality from Simon states that the results of our decisions depend on our human and environmental limitations and capacity, how and from where we collect data (quality of data), and how we process them. He says the result will always be bounded and limited because decision makers will choose the first solution that satisfies minimal expectations so it will not be the best but it can only be a satisfying one. Daniel Kahneman with his co-authors writes about that due to this the result will not be the same in each situation: "Clerks at a bank or a post office perform complex tasks, but they must follow strict rules that limit subjective judgment and guarantee, by design, that identical cases will be treated identically. In contrast, medical professionals, loan officers, project managers, judges, and executives all make judgment calls, which are guided by informal experience and general principles rather than by rigid rules. And if they don't reach precisely the same answer that every other person in their role would, that's acceptable; this is what we mean when we say that a decision is 'a matter of judgment'" (Kahneman, Rosenfeld, Ghandi, Blaser, 2016, p.39).

The level of using an integrated information management system at SMEs, which can be a source of data in a decision making process, depends on how big the company is. Smaller ones run their business often without well-organized business information, they only use accounting or financial software in many cases. Middle enterprises usually install an integrated system in the middle as a hub, with several satellite software around it and the Big Data solutions have been added to these systems in the last few years. These IT tools usually perform very demonstrative data visualization from the gathered data of the integrated management system but the usability of these charts is uncertain. In several cases the users of these systems have admitted that the main reason why they apply the result of the charts from Big Data tool is that it can be an evidence later if things occasionally go wrong. By now this problem has also been published in the most distinguished business journals, in the Harvard Business Review. “The conventional tools we all learned in business schools are terrific when you’re working on a stable environment, with a business model you understand and access to sound information. They’re far less useful when you’re on unfamiliar terrain – if you’re in a fast-changing industry, launching a new kind of product, or shifting to a new business model. That’s because conventional tools assume that decision makers have access to remarkably complete and reliable information. Yet every business leader we have worked with over the past 20 years acknowledges that more and more decisions involve judgments that must be made with incomplete and uncertain information” (Courtney, Lovallo, Clarke, 2013, p. 41). These conventional tools do not ensure that during the process of decision making, all data and expectations are provided since what is relevant is known by the decision makers from experience. The other issue is that they cannot quantify that how many times one of the data is more important than the other and this is against the tools based on scoring method and data-weighting, which are used by banks and financial organisations for example for risk analyses as mentioning another type of decision support systems.

In connection with the Big Data hype in the last decade, decision makers should take James G. March’s hint (1991) about the irrelevancy of the data, who says that the decision makers collect a huge amount of data, which play a very tiny role or do not play any kind of role in their decisions. It seems March’s models are still valid as Tanya Menon and Leigh Thompson write in their article on “How to make better decision with less data” (Menon, Thomson, 2016). They found that “despite all of the data available, people often struggle to convert it into effective solutions to problems. Instead, they fall prey to what Jim March and his co-authors describe as “garbage can” decision making: a process whereby actors, problems, and possible solutions swirl about in a metaphorical garbage can and people end up agreeing on whatever solution rises to the top. The problem isn’t lack of data inside the garbage can; the vast amount of data means managers struggle to prioritize what’s important. In the end, they end up applying arbitrary data toward new problems, reaching a subpar solution. To curb garbage-can decision making, managers and their teams should think more carefully about the information they need to solve a problem and think more strategically about how to apply it to their decision making and actions" (Menon, Thompson, 2016, p. 76).

According to March, who is best known for his research on organizational decision making, people can remember and recall colourful stories and information more easily than data of statistics. He published several books and articles about how we should think about decisions and decision making in organizations. He divided this into three major parts. "The first part is based on a vision of decisions as resulting from intendedly rational choice. Such a vision is the dominant portrayal of decisions in social science. This vision of decisions is elaborated by considering developments associated with problems of uncertainty, ambiguity, risk preference, and conflict. The second part of the story is based on a vision of decisions as driven by a logic of appropriateness implemented through a structure of organizational rules and practices, not by a logic of consequence. The discussion of rules and rule following is extended by considering the ways in which rules of behaviour evolve through experience, selection, and diffusion. The third part of the story examines ideas about decision making that challenge standard ideas of decision altogether, visions that picture the outcomes of decisions as artifactual rather than as central to understanding decision making. These visions are exemplified by discussions of networks, temporal orders, symbols, and the development of meaning" (March, 1991, p. 95). Probably we can explain the importance of story-telling and narratives in business decisions by this. Despite the popularity of "Profit First" – theory as a way to think about business, this view has not been adopted by many of those participants. There are people behind every decision with their symbols from their cultural and social backgrounds, with their religions and up-bringing as starting points of their expectations. I have to mention the process of knowledge representation when we create new symbols from the previous ones during the whole thinking process. Everything, between the input and output, belongs to the examination of thinking. Transformation of symbols always happens based on some sort of rules. According to Boole's concept every knowing is derived from logical and arithmetical operations (Velencei, Szoboszlai, Baracskai, 2014).

Knowledge representation opened the door for a new paradigm of decision support with the following essence. "Contrary to the world of IS/ICT there was much less change in the world of decision making. And contrary to the world of IS/ICT we believe that the world of decision making a paradigm shift is imminent. The essence of this paradigm shift is that in the era of knowledge abundance the models based on the idea of scarcity of resources are losing relevance and are bound to play lesser and lesser role. Our research to date shows that in smart decisions the emphasis is on behavioural patterns, behind which we recognize patterns of cognition" (Baracskai, Velencei, Dörfler, 2014, p. 401). Getting these cognitive patterns, a smart complex decision needs two essential elements. One of them is the experienced decision maker, and maybe some experts and peers from the company, as the most authentic information resources due to that there is everything in their mind and knowledge in *soft* form which is essential for the best result (instead of the countless numerical *hard* information), and just these *soft* data have to be systematized and transformed into applicable input for the reasoning part of the decision making process. First Michael Polanyi introduced the definite terminology for this when he wrote about *tacit knowledge* in his book titled Personal Knowledge (Polanyi, 1958). The other element is an appropriate tool which has to be able to handle these soft data and logical "if…then" rules, from which the knowledge-base of the complex decision will be built. But what type of the decisions can be smart? Certainly not every decision can be made smarter because many decisions do not need a process for getting the best result. Three decision types could be defined based on programmability and structuring according to Herbert Simon (1982), Figure 5.1. depicts the main features of these decision types.

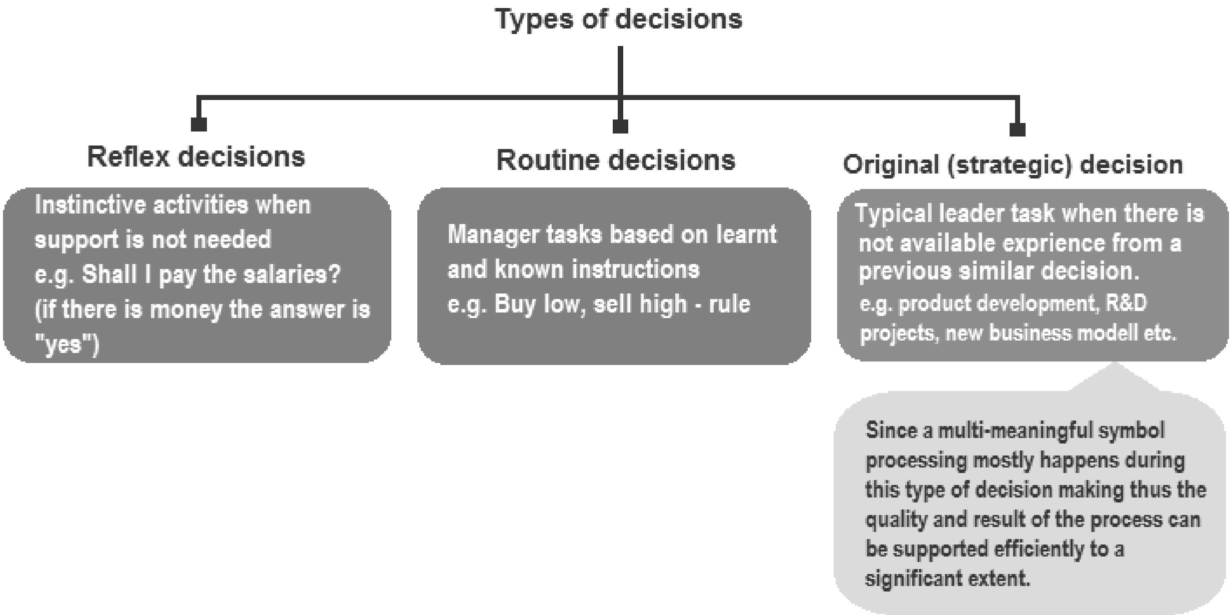


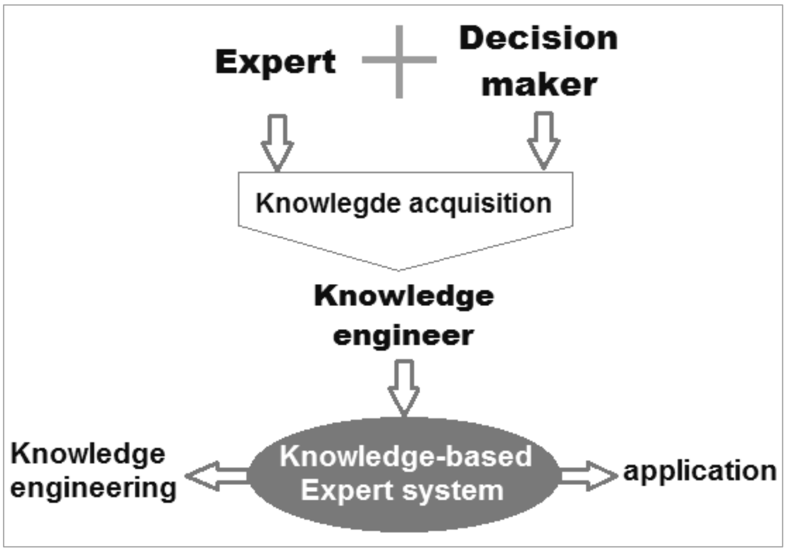
Image source: own research result

Figure 5.1. - Decision Types

The reflex decisions and the routine decisions belong to the “well-structured” problems because that they have a right answer but the original (strategic) decisions are so-called “ill-structured” or “ill-defined” problems thanks to that they do not yield a particular, certain answer.

5.2. Smart decision at an SME

Getting a convincing answer for my question, whether we can improve smart decisions efficiently at SMEs or not, I demonstrated it in a concrete business case. The examined company operates in a technology intensive field, it manufactures LED lamps and offers services in connection with this. Thanks to the expansion of the past few years the earlier place was grown out and they had to look for a new, appropriate place for their manufacturing activity. The ultimate goal was to support the decision maker in his dilemma where and how to place the new business unit? In this case “How” means what kind of financial construction to choose: renting or buying. I worked with the owner of the mentioned company. At the first step we collected all data: feasible alternatives (called “cases”), attributes (called “expectations”) and after I put them into a knowledge-base through a knowledge engineering process by the Doctus Knowledge-based Expert System tool (Doctus KBS, 2011). This tool consists of two parts, the knowledge-bases and the shell. The shell is an empty software, designed to build the knowledge-bases of the experts. Building a knowledge-base incorporates three processes: Knowledge Acquisition, Knowledge Engineering, which consist of systematization and fine tuning, and Application, all facilitated by Knowledge Engineer (See Figure 5.2). As Doctus’s developer defined “DoctuS, uses symbolic representation, that is to say symbolic artificial intelligence. The first advantage of symbolic representation of knowledge is that it’s humane. The symbolic logic is the only solution that does not quantify the user’s preferences. E.g. the person, whose knowledge is being modelled, thinks that the beautiful is a better value than the ugly. Nobody thinks that the beautiful is 3,6 times better than the ugly. Using symbolic logic we do state nothing like that. Into the symbolic knowledge base of an expert system we can put the knowledge in form as we talk or think about it. Therefore we get to the second advantage, which is the transparency, easy modification and fine-tuning of the knowledge base" (Baracskai, Velencei, Dörfler, 2005, p. 61).



Source: own research result based on Doctus documentation[1]

Figure 5.2. - Building a Knowledge Base

Making a complex business decision is required to acquire at least 15-20 relevant attributes each with 3 or 4 values to state that it is sophisticated enough. It is important to give a very familiar label to each attributes and values, it means the decision makers have to use their own expressions instead of conventional ones, and if any of them is too "neutral" the knowledge-base will not be comfortable. We have to consider that not only the number of attributes is decisive but their hierarchy and setup as well. It is particularly important to involve the experts of all main fields of the operation as finance, HR, marketing and so on, and to facilitate a successful collaboration for the sake of formulating the same understanding of the expectations like "financial benefit" is even more essential. Many researches have confirmed that when all experts participates in this phase of the process then the result will be more acceptable for the whole organization. The next step is finalization of the hierarchy of attributes, namely the deductive graph which is depicted in Figure 5.3.

As we can see 21 attributes were collected into four levels, so we can state that our decision is detailed enough. All aspects of business were included into the leaves of the graph as "financial conditions" aspect, "control" aspect, "prestige" aspect and "operability" aspect as

[1] Doctus documentation is available on: www.doctus.hu

well. There are several attributes which depend on another like “tender possibilities”, “real estate cost” and “labour cost” under the “financial conditions”.

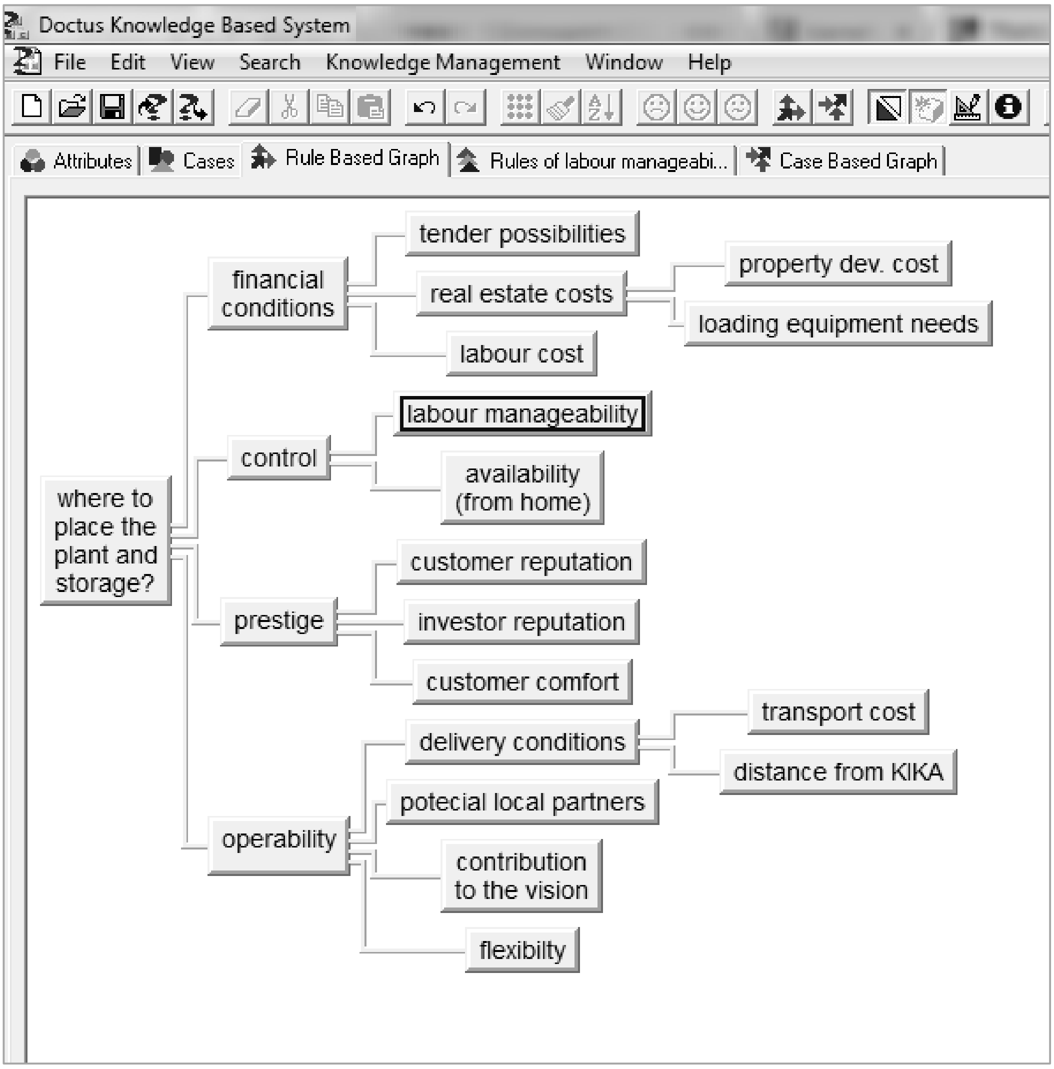
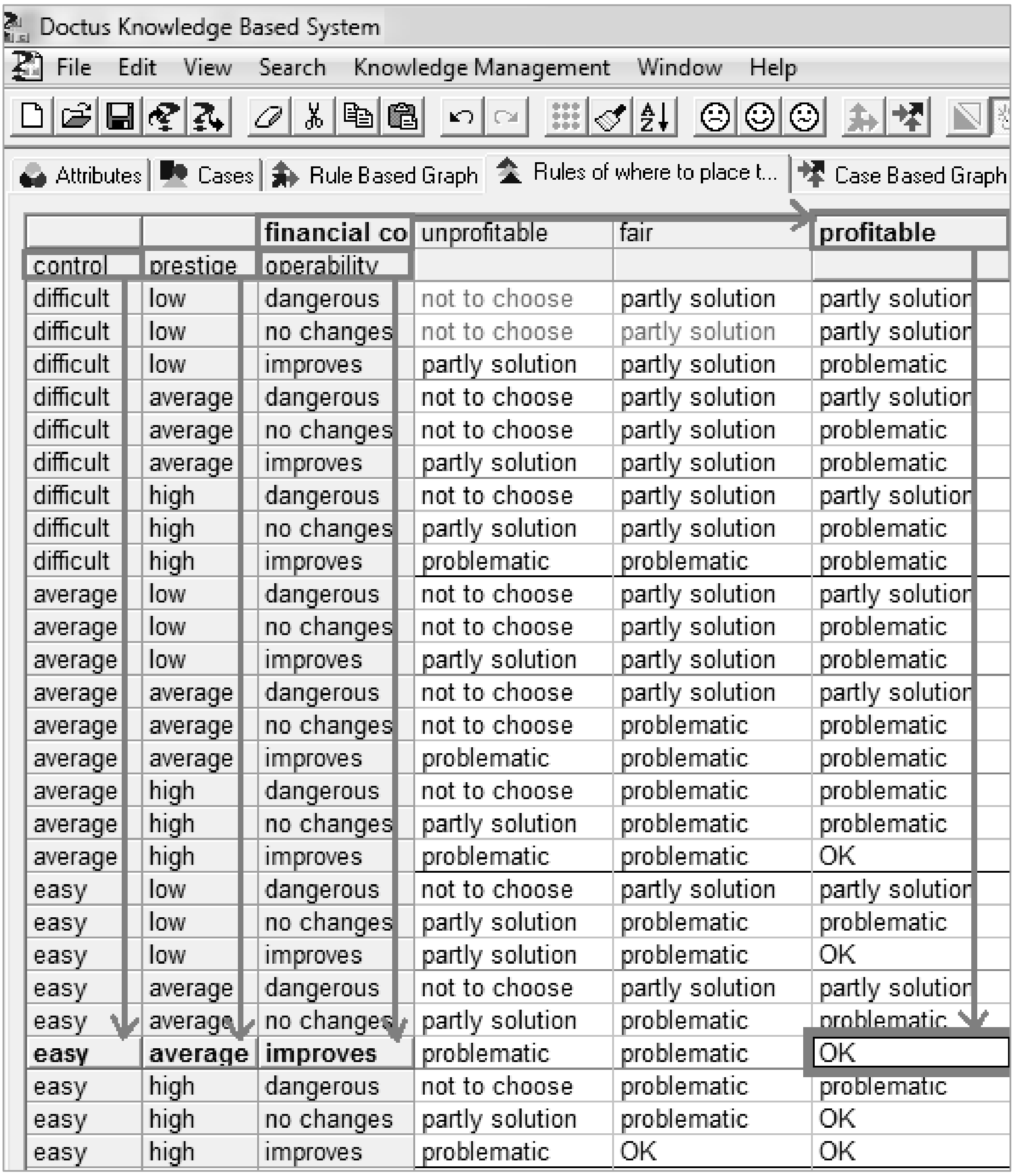


Image source: own research result

Figure 5.3. - Deductive Graph of attributes

After this we had to articulate the logical rules between the values of input attributes above into causal relationships. In a complex business decision an experienced decision maker does have 1000-2000 rules in their long term memory to be recalled to get the result. Certainly it is not necessary to articulate all rules one-by-one due to the machine learning system which can trigger the next suggested rules based on the previous submitted ones. This trial-and-correction process continues until the decision maker is satisfied with all of the rules. In the current case we articulated 231 rules to get this phase.

The evaluation of cases is called deductive reasoning. In this case, when there is no experience in the decision and we call the situation “original decision” (most of the strategic decisions belong to this group), deductive reasoning or rule-based reasoning is used. In my research the explanation of evaluation can be seen on Figure 5.4.



		financial co	unprofitable	fair	profitable
control	prestige	operability			
difficult	low	dangerous	not to choose	partly solution	partly solution
difficult	low	no changes	not to choose	partly solution	partly solution
difficult	low	improves	partly solution	partly solution	problematic
difficult	average	dangerous	not to choose	partly solution	partly solution
difficult	average	no changes	not to choose	partly solution	problematic
difficult	average	improves	partly solution	partly solution	problematic
difficult	high	dangerous	not to choose	partly solution	partly solution
difficult	high	no changes	partly solution	partly solution	problematic
difficult	high	improves	problematic	problematic	problematic
average	low	dangerous	not to choose	partly solution	partly solution
average	low	no changes	not to choose	partly solution	problematic
average	low	improves	partly solution	partly solution	problematic
average	average	dangerous	not to choose	partly solution	partly solution
average	average	no changes	not to choose	problematic	problematic
average	average	improves	problematic	problematic	problematic
average	high	dangerous	not to choose	problematic	problematic
average	high	no changes	partly solution	problematic	problematic
average	high	improves	problematic	problematic	OK
easy	low	dangerous	not to choose	partly solution	partly solution
easy	low	no changes	partly solution	problematic	problematic
easy	low	improves	partly solution	problematic	OK
easy	average	dangerous	not to choose	partly solution	partly solution
easy	average	no changes	partly solution	problematic	problematic
easy	**average**	**improves**	problematic	problematic	OK
easy	high	dangerous	not to choose	problematic	problematic
easy	high	no changes	partly solution	problematic	OK
easy	high	improves	problematic	OK	OK

Image source: own research result

Figure 5.4. - Explanation of the result

We can see in Figure 4 the conclusion of reasoning is satisfying thanks to that there is at least one case when the result is “OK”. If there had not been any, we should have continued the fine tuning on the rules to get into this stage. If we could get more than one result with

“OK”, we should also review our rules because in that case the decision maker’s way of thinking was not consistent enough. At the last point of the process to make the result accepted by the decision maker we analysed that what kind of influences were generated by each particular attribute on the output.

One of the benefits when we use Decision Support System (DSS) is that the decision will be transparent. It means we can follow the path of our thinking as changing one of the rules it will cause a modification in the result with different probabilities.

5.3. Conclusion

The obvious conclusion from this case was that the decision maker was satisfied with the result, he entirely accepted it, and as he said this kind of support meant a really useful guidance for him in his dilemma due to the detailed thinking process. He admitted that he would not have been able to systematize his experience in such a complete form without the DSS and the consultancy. The assumption that another SME in a similar dilemma could efficiently use the knowledge-base of this case, tends to confirm the usefulness of pattern recognition – the new knowledge. Some examples have already been available for these kind of collaborations (Lin, Nagalingam, Kuik, & Murata 2012) however there are also some new findings based on my approach with the knowledge-bases (Tsui, Wang, Cai, Cheung, & Lee 2014) or knowledge management (Lee, Foo, Leong & Ooi 2016). As Peter Drucker writes “Among history-making innovations, those that are based on new knowledge – whether scientific, technical, or social – rank high. They are the superstars of entrepreneurship; they get the publicity and the money. They are what people usually mean when they talk of innovation, although not all innovations based on knowledge are important. Knowledge-based innovations differ from all others in the time they take, in their casualty rates, and in their predictability, as well as in the challenges they pose to entrepreneurs. Like most superstars, they can be temperamental, capricious, and hard to direct. They have, for instance, the longest lead time of all innovations. There is a protracted span between the emergence of new knowledge and its distillation into usable technology” (Drucker, 1985, p. 75). According to Thomas Kuhn (1962) the new scientific theories based on individual inventions and discoveries, like knowledge-based innovations, need at least thirty years to become scientific principles. My main goal in this article is to introduce the new knowledge as the source of innovation and explain how it can help executives.

6. Discussion and conclusion

The title of the current thesis „Knowledge bases as a source of innovation" and the four problem areas introduced above cover the problem space which was disclosed on our research journey. My goal was to examine the decision makers' mindset patterns.

Three elements have an impact on the result of the dissertation:

- the model
- the tool
- and the method (algorithm).

First step of the decision support is to define the dilemma and expectations. These create the model of the decision. How the elements of the model are related to each other is described by the algorithm, and of course several algorithms can be used for this, and in the same way, we can run the same algorithm with different tools. In response to a question of whether the results of the dissertation would be different by using other deduction, induction, and reduction algorithms instead of those integrated into the tool current used, the following observation is valid. If the model changes, then of course the decision also changes. If the model does not change, but the algorithm changes, a different decision is made. If the model does not change, and the algorithm neither change, the decision does not necessarily have to change, but usually it changes. It is certain that the representation of the decision will change. In my case Doctus KBS was the tool. Doctus is actually a Knowledge-Based Expert System Shell. Being a shell means that Doctus is an empty software, which consists of two major parts, the Knowledge Base – it is some kind of container of knowledge – and the shell, in which the ID3 algorithm is integrated, as a method. This Knowledge-based Expert System with these two parts has already been proven in more than 160 cases, it brings a satisfactory solution to the examined decisions. Certainly, I could have done this with other tool from the expert systems by another algorithm. Of course, in this case the result of the dissertation would have been different: the representation or we can say that, the visualization would look different, so the result would have to be read differently, but it is sure that, in any case the same mindset patterns would come out.

This work comprises four studies which investigate Knowledge-based Systems as tools, Knowledge Acquisition as method, applications as cases, or Knowledge Engineering as a role in the field of decision support. I argued that understanding and supporting the decision-makers' thinking and mindset require a transdisciplinary approach, that is the reason why the presented set of papers draws upon organizational behavior, artificial intelligence, behavioral economics, knowledge management and computer sciences among other disciplines. These papers illustrate different deliberations about decision support with the experienced decision maker in focus. Based on the problem areas examined, we have drawn the appropriate conclusions and outlined possible further directions for research on each topic, which could be valuable contributions to the disciplines listed above.

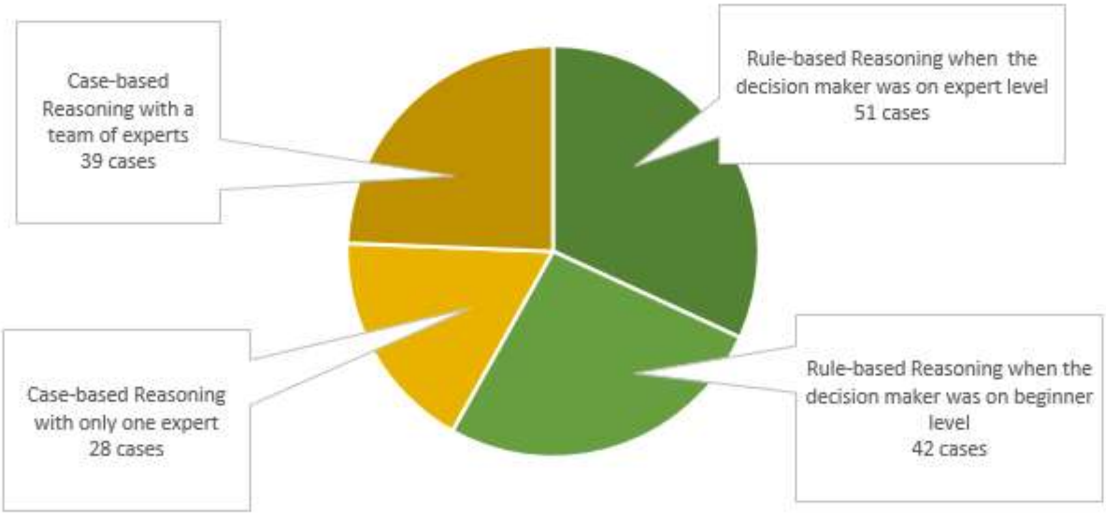
By the first paper (Chapter 2), we start with a broad focus as we try to give a comprehensive picture of the problem domains and business sectors in which these processes and systems can be successfully applied (Table 6.1.).

Problem domain	**Business sector**							
	Telco	Automotive industry	Pharmacy	Public	Trade	Energy	Sport	Finance
Investment	16 (RBR)	10 (RBR)	4(RBR)	3(RBR)	3(RBR)	15(RBR)		
Financing				2(RBR)	19(CBR)			3(RBR)
R and D	8 (RBR)	2 (CBR)	12(RBR)	3(CRB)		1(CBR)	4(CBR)	
HR	24 (18CBR+6RBR)		16(12CBR+4RBR)	7(4RBR+3CBR)		3(CBR)	5(CBR)	
Total	**48**	**12**	**32**	**15**	**22**	**19**	**9**	**3**

Table 1

Table 6.1. - Problem domains and business sectors

Based on the direction of logic, in our research we made a distinction between Rule-based reasoning and Case-based reasoning and we also had to distinguish between the expert or beginner level of the decision maker with whom we conducted the process. Based on these, we worked with the following cases (Figure 6.1.).



Source: own research result

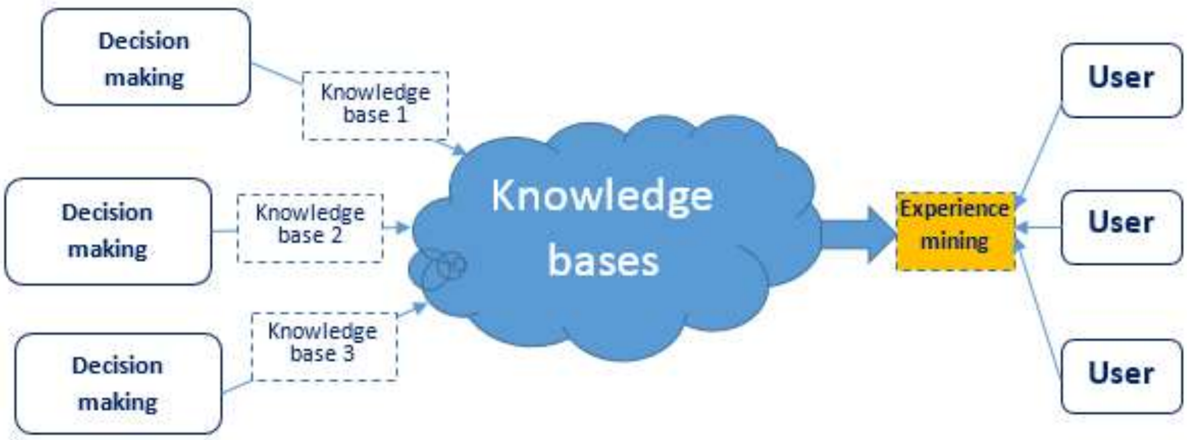
Figure 6.1. - Distribution of examined cases within the total sample

We demonstrated some concrete examples with the associated graphs and the resulting rules. Based on a case study research with 160 applications, we draw two conclusions in connection with the Knowledge-based Systems. On the one hand, the key to better usability is that an easy-to-understand user interface is needed to present the results of the process. When the result is difficult to interpret and the decision maker has to rely entirely on the explanation of an outside person (who handles the system), it reduces acceptance and the real understanding of the result. On the other hand, in order to design an interface for a system, which is based on complex mathematical algorithms that can also be used by people who are not trained for it, it is necessary to involve those who actively help the decision makers in the processes into the design. Such as Knowledge Engineers, who exactly see where the critical points are during the process when the decision maker really understands the result or just listens to it. This is a challenging task, since human thinking and an artificial intelligence-based inference must be demonstrated in such a way that the decision makers can recognize their own thoughts.

There could be several relevant future directions of this research. On the one hand, it would be interesting to examine in detail which methods and tools work better, or we can also say which results are better accepted in practice: those, which were presented in our cases or decisions made automatically based on big data? There could be another convincing R&D project to develop a knowledge-based expert system from the beginning, with the involvement of end-users, i.e. decision-makers, designed by professional user experience designers so that even end-users can use it independently.

In Chapters 3,4, and 5 we focus on the detailed and factual presentation of some applications of the examined problem areas. Each presents an example, but all of them are different from some aspects, for instance, the method or the direction of the reasoning as Case-based Reasoning, Rule-based Reasoning or a unique method, Case-based Rule Reasoning, which we can call reduction.

In Chapter 3, we show a concept about an alternative way of using the Knowledge-based Systems, when KBSs are built into a smash-up architecture. In this chapter, we discuss the comparison of our concept and the existing systems which recommend contents based on weighting and frequency and we try to highlight the main differences. This paper focuses on the possibilities of innovation and knowledge creation but does not consider all details of the development. However, due to the lack of empirical data, we cannot draw a conclusion from this concept based on a real usage of the platform, but we introduce a method with a whole new perspective, which could be experience mining. Experience mining could be a form of superintelligence after Bostrom (2014) if it could work as in the Figure 6.2. and we think this concept is a highlighted unique thought of this thesis.



Source: own research result

Figure 6.2. - Concept of experience mining

As we can see, members of the knowledge community (users marked in the figure 6.1.) can learn from the other’s knowledge or experience and it will shift the personal knowledge creation to a more collaborative model within the informal learning. In this form, the common knowledge base can become the source of innovation by giving new ideas for consideration, it can be the starting point of the novelty. In this case, the next step in the research could be the development of the collaborative knowledge platform itself, which could be used to examine the presented concept of knowledge creation, the learning routes and experience mining. It would be interesting to examine whether the shallow knowledge mentioned in the paper deepens in topics that users find interesting, and which forms of contents help learning the most: pictures, texts, videos, or others.

In Chapter 4, we draw some conclusions from a case-based project evaluation at a University laboratory. The goal of this paper is to lay out an approach to evaluate R&D projects by cases with the help of the project managers, where, on the one hand, the lack of big data and, on the other hand, the project operation of the organization urges the project evaluation by a Knowledge Engineering process. The outcomes of this examination can be used as a promising starting point of future strategies in project planning and maybe in innovation management at R&D laboratories of Universities. This approach can be used in any kind of project evaluation when knowledge management happens, or organizational learning and knowledge creation is required based on results and the experience of team members and project managers. This paper describes the final results of a two-step research. In the first phase, we examined the question of how to build a consistent knowledge base from the interviewees' mindsets, which will finally give the same sensemaking for all of them (see the script of the interviews in Appendix 8.1). Accomplishing this is a key point of knowledge creation according to Weick's novel approach to the redefinition of learning (Weick 1991). Our observation from the first phase (Tóth-Haász et al. 2019) is that individuals can only think through certain concepts or terms if they understand them, or, we can say, when it became part of their personal knowledge. In a case where the words are put into their mouths and they just accept them without any real conviction, their personal knowledge growth is not ensured. From the interviews, the second finding was that each of the participants has their own stories with different issues and their used phrases were a bit diverse, but it could be definitely felt that they were socialized in the same terminology and this allows a common project evaluation with them.

Based on the results of the second phase of the research, we have some conceptual and practical implications. To support these, we developed a concept matrix of our topic applying the work of Webster and Watson (2002, p. 17) with the definitions of the key terms (see the table in Appendix 8.2.) In this phase, we aimed to examine the most informative attributes in R&D projects of university laboratories and the logical relationship between them. We found that the project manager’s experience and the team leader’s relationship to the topic are the keys which have the most significant impact on the success of the investigated projects. In this paper, we give a detailed comparison of academic projects and projects in an industrial environment, since, academic project managers seek challenging projects from the aspect of their own research field. In accordance with the rules found, to successfully operate an R&D project in an academic environment, the team leader must be “enthusiastic” about the topic and not be “forced to commit” to it. However, it seems obvious that the commitment and the passion of the project manager are key success factors of any project, this is particularly true for the success of reverse projects in university laboratories, which are actually D&R projects. In this context, D&R project means that, first, the University laboratory executes a development for a semi- or ill-structured problem and after this, in a second phase, Homo Academicus establishes a research project motivated by his or her scientific curiosity. As a finding of this research, this reverse process is one of the main differences from the point of the projects. Our managerial implications suggest the Knowledge Acquisition as an adequate method in situations when appropriate hard data are not available to evaluate projects but the project managers’ knowledge and experience can be incorporated through interviews. This method can also be applied as an additional one within the current project closing and evaluation procedure in cases when there are abundant data from project management systems, but the organization can also facilitate knowledge creation based on the projects. We believe that this finding can be a value-added contribution to the body of the knowledge of the Project Management.

The goal of this paper is to give different understandings of the presented approach of project evaluation. This study arguments the theoretical interpretation of four perspectives and each of these points at its own reasoning of why this project evaluation method can be adequate in R&D projects in University labs. According to Hanisch and Wald’s study (2011), which aims to demonstrate a framework for project management researches, a theory-based transdisciplinary approach and by this, further disciplines is called for integrating. This appeal meets with our research as shown is the Table 6.2. In Hanisch and Wald’ paper, based on a relevant comprehensive literature review, the authors investigate some theoretical perspectives which are also appropriate to considering to our research. Their study cites and relies on other classification of the perspectives on projects (Turner et al. 2010; 2013) representing theory of nine schools of project management or Bredillet’s work Based on these sources the following theoretical perspectives are identified:

1) Behavioral theories

2) Human-computer interaction

3) Theory of the nine schools of Project Management

4) Organizational learning

These different perspectives exist in three levels: the individual as micro, organizational as meso and social as macro, and all of them relate to the “allied disciplines” of Project Management (Kwak and Anbari 2008): 1) Behavioral theories reflect neoclassical economics, more precisely behavioral economics, which built a bridge between the economic and psychological analyses of individual decision-making; 2) Human-computer interaction reflects to Artificial Intelligence; 3) Behavior school (The Project as a Social System) as one of the nine schools of Project Management reflect some distinct disciplines within social sciences and management; finally 4) Organizational Learning perspective relates some current trends of Knowledge Management.

Theoretical perspective	**Individual level**	**Organizational level**	**Social level**
Behavioral economics	It focusses on individuals who decides based on bounded rationality It assumes that individuals decide by the cognitive limitations of the mind	It focusses on organizational structures and rules; It attempts to support decision based on the individuals’ knowledge	Psychologists distinguish between two kinds of theories: normative and descriptive. (Thaler 2000 p 138)
Human-computer interaction	It assumes that a software won’t decide instead of the individual (as decision-maker). They need a tools which is able to follow and interpret their	It assumes that a common Knowledge-base can contain all the organizational knowledge and the earlier results	It assumes that technological progress and wisdom change at different speeds which can create conflicts with our

	thinking and which can help to avoid cognitive biases by systematizing their knowledge elements		understanding of wisdom (Sapiens et al. 2019)
Behavior school within Theory of the nine schools of Project Management	It assumes that individual a member of the project team It assumes that developing relevant competence on levels of individual (and on all other levels) is a key for better performance (Gareis and Huemann 2007)	It attempts manage relationship between people on the project It focusses on organizational behavior, team building and leadership, communication and human resource management (Bredillet 2008)	It addresses the issue how to combine the nine schools of project management and integrating them into a complete system
Organizational learning	It focusses on the individual's tacit and explicit knowledge It attempts to utilize the tacit knowledge of the individual	It tries to address issues of measurement of its effectiveness; It uses classical knowledge management practises; It focusses on the context in which projects are executed (Schindler & Eppler 2003)(Rahmandad	It assumes that "Homo Economicus will become a slower learner" (Thaler 2000 p 135)

		2008)(Grapher 2004a)	

Table 6.2. - Theoretical perspectives in three levels

Similar to other studies, this one also has its limitations, which can define the direction of future steps. First, the sample comes from only one university. If we could compare the presented results to other university labs, we may receive confirmation for the attributes and the rules or new ones would come up. Second, the projects-as-cases are in the same domain in our research to ensure the consistency of the knowledge-base. According to Holsapple's study, domain complexity strongly influences the quality of knowledge acquired (Holsapple et al., 2008). All of them are engineering R&D projects, dominantly in the automotive industry. It would be interesting to investigate the results in other domains, such as software engineering or architecture in order to know whether the experience of the project manager is equally emphasized. Finally, comparing the findings of the presented project evaluation process to its industrial counterpart would be a very advantageous initiative. This means an examination with the same method on the same projects but with the project managers of the customer side. These future research directions could confirm both the validity of the presented method and the result of the evaluation.

In Chapter 5, we aimed to understand the decision maker's mindset in a complex thinking process about where to place a new business unit. We helped him to consider all decision alternatives from different viewpoints and systematize the prior knowledge. He had specific ideas for each of the alternatives for locating the headquarter, warehouse and manufacturing unit in rural and Budapest locations. During this consultancy, we organized four meetings with the CEO of the company and we followed him step by step from gathering the aspects to be thought through to the final conclusion and its acceptance. The clear conclusion from this case was that the decision maker was satisfied with the result, he articulated that, from the beginning, this result was in his mind, he just could not explain it explicitly and therefore he was not sure of his decision. By making it transparent and traceable for him, he was already fully convinced that this was the right decision and hence, he entirely accepted it. He said that this form of support was a really useful guidance for him in his dilemma thanks to the systematic thinking process. He admitted that he would not have been able to systematize his experience in such a complete form. As a forward-looking conclusion, we assume that another decision maker in a similar dilemma can effectively use the knowledge base of this case, and thus we return to the conclusions of Chapter 3 above and we confirm the usefulness of pattern recognition, which may be new knowledge. Finding clear justification for this assumption could be the future direction of this research.

Dilemmas are diverse, but they have one thing in common: the decision is always a choice between different alternatives. In this thesis, we presented an approach, a method, and a tool that can effectively support this choice when there is available experience but the working memory needs to be supported. We do not claim that the presented method or tool can be used most effectively in all decision-making cases, but we believe that the few examples demonstrated highlight that this form of decision support can be applied in practice and is also an area worth researching.

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8. Appendix

8.1. Interview script

Duration: approx. 1-1,5 hours

Step 1:

introductions (approx. 10-15 minutes)

…We are conducting a research about the evaluation of R&D projects at the University on behalf of "XY" in the "Z" program. The research aims to evaluate the finished projects in order to get the key aspects which have the most relevant impact on the success. Now we should talk about some projects, and we will submit some data into a Knowledge-base, and finally, the tool will systematize the data and it will run a reasoning. At the end, we will organize a workshop where we would like to evaluate the results together.

… The purpose of this interview is to gather and learn about the aspects of your project in detail. It is important to talk about closed projects, but whether it was a successful or unsuccessful project in the end is irrelevant.

Step 2:

the interviewee informally, free of constraints talks about his status at the university and hir/her projects (approx. 10-15 minutes)

… since when he/she has been working at the university as a Project Manager and a researcher (research field, graduation etc.)

…how many projects he/she has participated in as a project team member (not in a project manager role)

…how many projects he/she has participated in as a project manager

…select a project and tell us about it in detail: Who was the client? What was the goal? What was the management like? etc.

Step 3:

We show the current state of the knowledge-base and ask him or her the appropriate questions based on it (approx. 30-40 minutes)

…What do think about a result of your project? Was it value1/value2/value3? (Assigned to the attribute) If necessary, we briefly explain the meaning and content of each value based on what was discussed in previous interviews.

When he or she selected a value but seems uncertain in the answer, we make sure with clarification or verification questions that he/she has indeed chosen the adequate value.

If the conversation reveals that none of the values in the knowledge base is appropriate, we add a new optional value and enter the answer by the new item.

We go through all the aspects and select the appropriate values in the same way or supplement the set of values.

Once we have gone through all the aspects in the knowledge-base, we ask if there are any other attributes that he or she thinks relevant in order to get a complete description of the project (Is it necessary to add something to the list of attributes? If so, we also cross-check the answer with checking and clarifying questions, whether it is really necessary to add the new element, or whether it would be satisfactory for him or her to rename an existing element or add a new value.)

If we make sure that the new element is really needed, then in order to make a comprehensive evaluation we also have to ask about the new aspect related to the cases already recorded earlier.

Step 4:

Closing the interview (approx. 5 minutes)

After systematically going through all the elements of the knowledge-base, we ask him or her once again to think about whether all the relevant aspects have been considered, what has been left out in terms of evaluation, and how to improve the operation of the projects.

Recording the case in the knowledge base.

8.2. Concept matrix of the research

We made the concept matrix of our R&D project evaluation topic applying the work of Webster and Watson (2002, p. 17) with the definitions of the key terms. Table 1 highlight the following literature for further analysis:

Keywords Resources	R&D project and university	Project evaluation	Knowledge Acquisition	Academic communities
The Journal of Technology Transfer	Bozeman (2013)			
Academy of Management Perspectives	Bansal (2012)			
Industrial Marketing Management	Canhoto (2016)			
Technological Forecasting and Social Change	Fuster et al. (2019)			
International Journal of Project Management	Khedhaouria et al. (2017)			
Procedia - Social and Behavioral Sciences	Mahmood et al. (2014)			
Procedia - Social and Behavioral Sciences	Stukalina (2016)			
Research Policy	Szűcs (2018)			
Journal of Product Innovation Management	Un (2010)			
Procedia - Social and Behavioral Sciences	Yumusak et al. (2015)			

Decision Support Systems	Wang et al., 2017			
Procedia Computer Science	Fernandes et al. (2018)			
R&D management	Poh et. al (2002)			
Project Management Journal		Anbari (1985)		
International Journal of Project Management		Costantino et al. (2015)		
Omega		Eilat et. al (2008)		
Expert Systems with Applications		Feng et al. (2011)		
International Journal of Project Management		Ghapanchi et al. (2012)		
Omega		Karasakal, E., Aker, P. (2016)		
International Journal of Project Management		Liu et al. (2019)		
European Management Journal		Müller, R., Turner R. (2007)		
Decision Support Systems		Tian et al. (2005)		
International Journal of Project Management		Westerveld (2003)		
Knowledge Acquisition			Boose (1989)	
Decision Support Systems			Chua et al. (2012)	

Expert Systems with Application			Holsapple et al. (2008)	
Springer Science & Business Media			Kidd, A. (2012)	
Journal of Workplace learning			Lämsä, A., Sintonen, T. (2006)	
Human-Computer Interaction			March (1991)	
Human-Computer Interaction			Sapiens et al. (2019)	
Data & Knowledge Engineering			Studer et al. (1998)	
Expert Systems with Application			Wagner (2017)	
Expert Systems with Application			Wang et al. (2011)	
International Journal of Information and Decision Sciences			Zaraté, P. and Liu, S. (2016)	
International Journal of Project Management				Andersen E.S. (2016)
Homo Academicus Cambridge: Polity Press				Bourdieu 1988
Higher Education				Jessop 2017
Critical Policy studies				Jessop 2018
Academic Capitalism: Universities in the Global Struggle for Excellence: Routledge				Münch 2013

International Journal of Project Management				Savelsbergh et al. (2016)

Concept matrix of the research (own source based on Webster and Watson's study)

8.3. Doctus KBS

The research and examples presented and included in the dissertation were performed with the Doctus Knowledge-Based System. Since, the description required to understand the operation of the system would unnecessarily load the scope of the dissertation, we put these parts into the appendix here.

The sections that appear here are available at: www.doctus.hu/eng

Doctus KBS

…There are three types of reasoning in Doctus:

- If the expert can articulate the important aspects of the decision as well as the rules, the system will trigger these rules to get the evaluation. This is called *deduction* or Rule-Based Reasoning. It is used when there is no experience in the domain, therefore the situation calls for Original Decision.
- If the expert can articulate the aspects but he cannot say which of them are important and he cannot articulate the rules, though he is experienced enough (a few dozen cases with evaluation) this experience can be used to find out the rules describing the cases of his experience using *induction*, which is the symbolic version of Case-Based Reasoning. As there is extensive experience in the domain, the situation is described as Routine Decision.
- From the result of induction the important aspects of the decision can be determined using *reduction*. This is the third type of reasoning, though as it can only follow the induction, there is no third type of knowledge base, only two sorts of knowledge bases are built: rule-based knowledge base and case-based knowledge base.

Original Decision (when there is no experience in the domain)

When there is no experience in the domain the expert is to define the rules, therefore reasoning in this situation is called Rule-Based Reasoning. As it is started from the generalized rules, which are later applied to particular cases, it is also called deduction.

Acquisition of Attributes

Knowledge Acquisition always starts with formulation of the aspects of the decision. Aspects are given by the expert as attributes (i.e. the names of the attributes) and their values. A value of an attribute is a decision criterion. The acquisition of attributes and their values happens on the first pane of Doctus named “Attributes” Different orders of the “goodness” of the values of the attributes are available: it is increasing, when the first value is the worst; decreasing, if the first is the best one; if one value is not better then the other one, the order is nominal. Once the attributes and their values are defined, if we are building a rule-based knowledge base, the next step is to determine the dependencies between the attributes. This consists of two parts: the “which(s)” and the “how(s)” of dependencies.

Hierarchy of the Attributes: the Rule-Based Graph

The “which(s)” attribute dependencies means to allocate for each attribute on which other attributes it depends on. This is done by constructing a hierarchy of attributes called Rule-Based (or deductive) Graph on the third pane of Doctus, named Rule-Based Graph.To construct the graph, drag-and-drop is used.

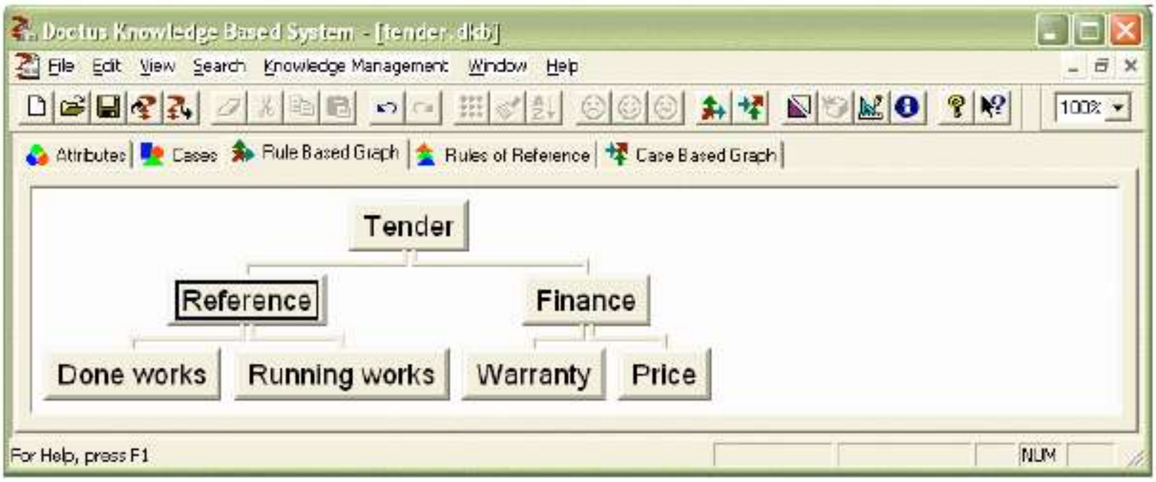

Figure G-3: The Rule-Based Graph.

If attribute B is connected onto attribute A (which means that A depends on B), then B is called factor of A. The same attribute may factor of different attributes, though not to itself (directly or indirectly). The root of the graph is not a factor of any other attribute; it is called decision attribute, or outcome. The leaves of the graphs have no factors, they are the input attributes. There will be attributes, which’s are factors of other attributes and having factors themselves; these are the dependent attributes. When the Rule-Based Graph is constructed, rules are to be defined in each node of the graph.

Acquisition of Cases

Knowledge-based systems are used to reason about cases. Cases can be anything that we can describe from all important aspects (i.e. defined attributes). One value of every attribute is assigned to each of the cases. Actually one value is the default but Doctus can also handle "Unknown", "Don't care" and distributed values.
The acquisition of cases happens on the second pane of Doctus, named "Cases". In deduction or Rule-Based Reasoning it follows the construction of the Rule-Based Graph; however, new cases may be added to the knowledge base at any time.

The Rules

Selecting an attribute on "Attributes", "Cases" or "Rule-Based Graph" pane, the name of the fourth pane changes, incorporating the name of the selected attribute in "Rules of…". (See Figure G-3) In each node of the graph (so for each dependent attribute) a set of rules is to be given, to assign an outcome (a value of the selected attribute) to each variation of the values of the factors. If a rule connects one value of each factor, it is called elementary rule.

Maths *:*

Use the markings: Attributes: A, B, C, ... (X is the decision attribute)

Values: A={a1, a2, a3, …}; B={b1, b2, b3, …}; … X={x1, x2, x3, …}

Rules: $A=a1 \wedge B=b2 \wedge C=c1 \wedge \ldots \Rightarrow X=x1$

Read: If A is a1 and B is b2 and C is c1 and … then X is x1

If a rule covers a range greater then one single value for at least one attribute, it is called complex rule. The covered range may contain neighbour values only; it may be closed (between two values) or opened (worst or better then one value).

Maths *: Use the markings from above.*

Rule: $A \in [a2, a5] \wedge B=b2 \wedge C=c1 \wedge \ldots \Rightarrow X=x1$

Read: If A is between a1 and a5 and B is b2 and C is c1 and … then X is x1

Rule: $A \geq a2 \wedge B=b2 \wedge C=c1 \wedge \ldots \Rightarrow X=x1$

Read: If A is better or equal to a2 and B is b2 and C is c1 and … then X is x1

The complex rules can be seen as aggregations of elementary rules. The knowledge is easier to describe if it is done by fewer complex rules. Of course the same knowledge can be described by different sets of complex rules, i.e. the elementary rules can be variously aggregated.

Doctus provides two different surfaces to handle rules; the user can switch between them. On 1D surface rules are presented in form of rule list, new rules may be defined editing them directly into the table or using the insert new rule command. (See Figure G-7) On 2D surface some of the factors will indicate the rows and others the columns of the table. Each cell of the table is a rule, its inputs are defined by its position (row and column) and the user defines the output selecting a value from the right-mouse-click-menu. (See Figure G-8) More than one cell can be selected at the same time.

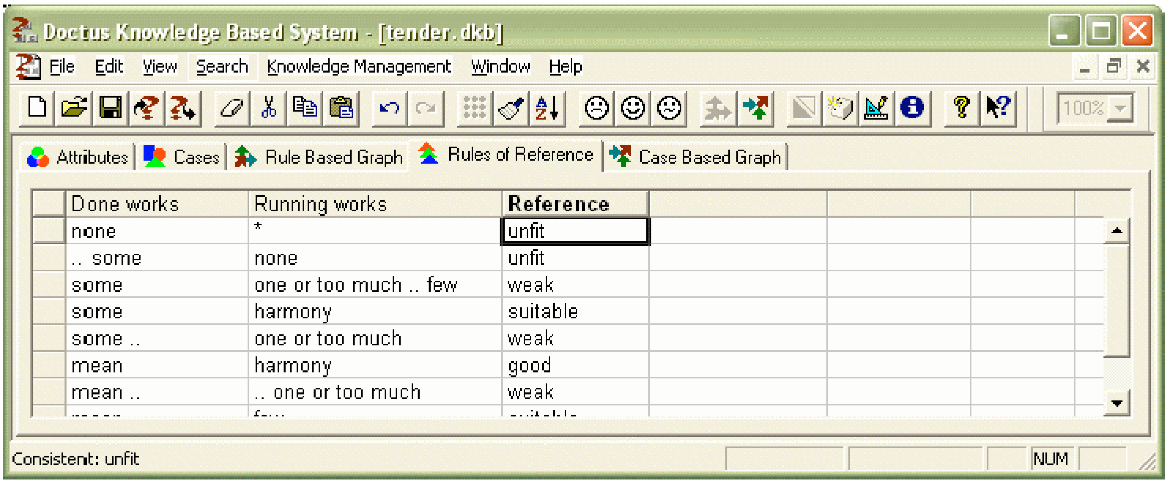

Figure G-7: Rules in 1D.

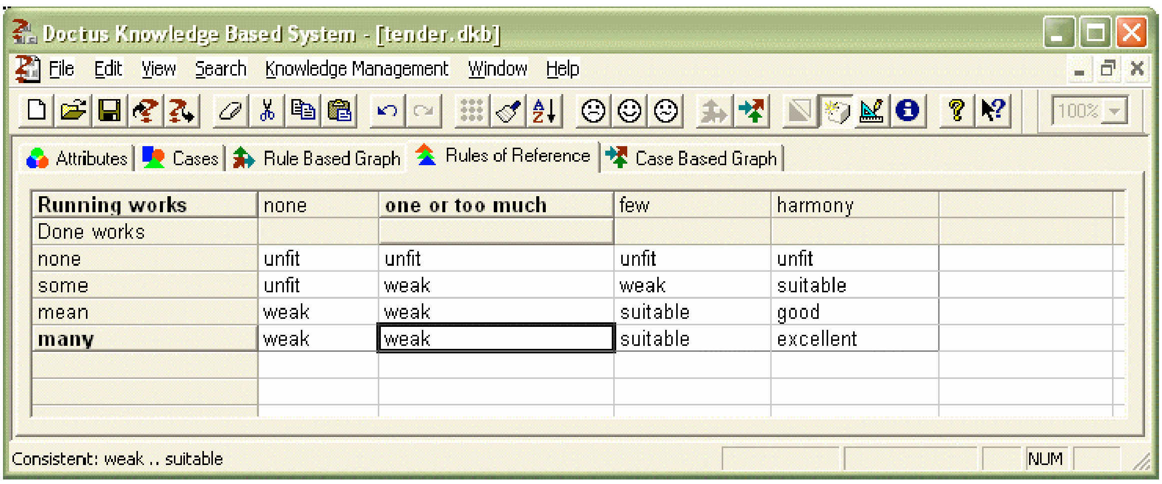

Figure G-8: Rules in 2D.

The Reasoning

Reasoning in a Rule-Based system is done by triggering the rules for the cases, getting a value of the decision attribute for each case; therefore it is also called evaluation of cases. The results may be seen on the “Cases” and on the “Rule-Based Graph” panes.

Routine Decision (when there are few dozen cases in the domain)

When the expert cannot or do not want to define the rules, though he has a few dozen of cases with evaluations in his experience, these cases can be used to find the relations between the values of the attributes. The basis of the reasoning are the cases, therefore this kind of reasoning is called Case-Based Reasoning. As the set of particular cases is used to find generalized rules, which’ describe it appropriately, it is also called induction.

Benefits

The more obvious benefit of the case-based knowledge base is that the number of used attributes is reduced, to the informative ones. This makes the deputation of a decision much easier. Naturally, it is nothing of the sort of making programmed decision makers, as the Case-Based Graph represents the only the expert’s experience at given conditions. If a new case appear, which cannot be described with the knowledge base, it means there were no similar cases in the expert’s experience. The conditions may also change. Thus it is highly recommended to add the new cases constantly to the knowledge base, to maintain it as fresh as possible. The greatest benefit of the building a case-based knowledge base is less obvious. This process is almost always accompanied with knowledge discovery, that is to say it makes a part of tacit knowledge explicit. It is very common that the expert is astonished at the first sight of the Case-Based Graph, thus the fine-tuning is not only necessary to make subtle adjustments to the knowledge base but also to get a deeper understanding of the result.

Acquisition of attributes and cases are similar to presented above.

Decision Tree: the Case-Based Graph

Doctus generates the Case-Based Graph classifying the cases acquired from the expert. The Case-Based Graph is a decision tree; it does not show dependencies but the “if… then” rules induced by processing the cases. The “if… then” rules may be read from the root of the graph towards its leaves, where the value of the outcome is shown. There are three alternative branching methods to generate the Case-Based Graph: The default is called “Efficient”, which is described in the following chapter. The “Bipolar” makes two branches for each node, grouping the values of the attributes to bad and good. The “Heuristic” provides the same result as “Efficient” if there is a great amount of cases and/or attributes, which would otherwise highly increase the computing time. The attributes appearing in the Case-Based Graph are called informative attributes, as they are sufficient to classify all the cases.

Classification of Cases

After all, how the Case-Based Graph is constructed? Let’s presume that all cases form a disordered set, where the order is defined as homogeneity by benchmark values (values of outcome attribute), which means that cases in one subset have the same benchmark value. The attribute is searched, which contributes the most to the order. The attributes are taken one-by-one forming subsets according to their values. Their strength in making order is measured by an entropy-gain (informativity) calculating algorithm. The most informative attribute is chosen (the root of the graph) and the first level subsets are formed according to its values. These subsets are further divided using the same algorithm until all subsets are homogenous by benchmark values. When a homogenous subset is formed, it is not further divided; it will be a leaf of the graph.

The Reasoning

The result of the Case-Based Reasoning is the Case-Based Graph, which describes the rules induced from the cases of the expert’s experience. It is easy to reason about new cases using the Case-Based Graph as well: the new case simply has to be positioned according to its features by the informative attributes, following a path from the root to a leaf of the graph. However, classification of new cases in Doctus is facilitated with reduction and with some of the Knowledge Export solutions.

Decision Analyses and Fine-Tuning

It is usually not easy for the expert, that his experience may be described with only a few of the attributes he defined. Analysis of the Case-Based Graph is facilitated with hands-on information provided by Doctus about the informativity, density, cases and statistics for the nodes of the graph. It is easy to change the attributes in the nodes of the graph, though there are conditions, which are likely to be observant of. The fine-tuning is switching between the parallel or nearly parallel knowledge models. This means that the swaps of the attributes in the nodes of the graph are justifiable only if they are of equal or nearly equal informativity and density.

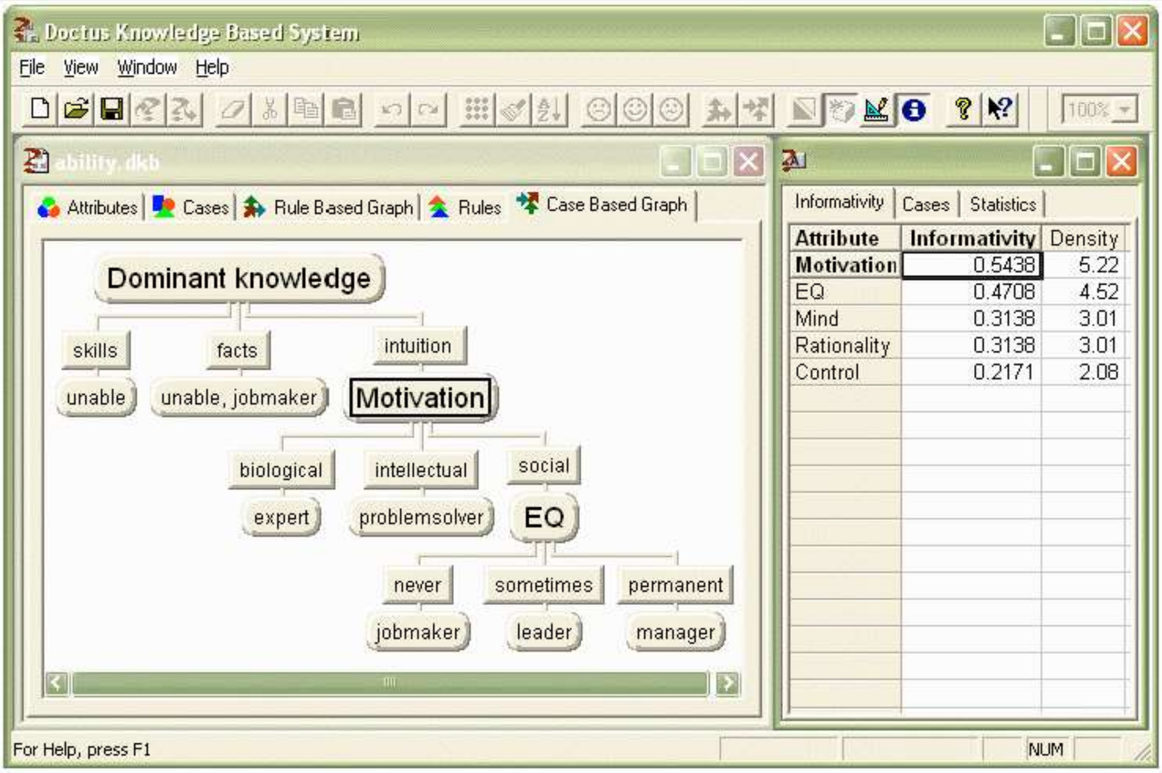

Figure G-20: Informativity and Density of the Attributes.

There are also another ways of fine-tuning: Sometimes a case is found, that cannot fit the set and makes serious degenerations to the Case-Based Graph. These cases usually cannot be described with the attributes defined, thus we call them odd-one-outs. The solution for these is to be excluded from the set used as bases for Case-Based Reasoning. Sometimes two (or more) cases are found, that are completely the same, except for the benchmark. It usually means that a new attribute or a new value is needed to be defined, which distinguishes the cases in question. The cases themselves may be modified as well.

Learning from Cases (reduction of the model)

Once the expert accepted the Case-Based Graph, a new rule-based knowledge base can be created, which contains only the informative attributes but gives the same evaluation for the cases as the ones used for the induction of rules. The reasoning uses rules but they are induced from the set of cases, thus this type of reasoning is called Case-Based Rule Reasoning. As the knowledge base is generated automatically by reducing an existing model, it is also called reduction.

Benefits

The great benefit of the Case-Based Rule Reasoning is the reduced size, i.e. the significantly decreased number of the attributes. It enables the user to make a quick evaluation of new cases but attention is to be paid to possible loss of actuality. To avoid the use of outdated knowledge base, the original case-based knowledge base is to be maintained, constantly adding the new cases and regenerating the Case-Based Graph. If the conditions are changed, the Case-Based Graph will alter.

Missing or Indefinite Rules

If there were value ranges of some rules not covered or multiply covered by cases used for Case- Reasoning, in the rule set of the reduced knowledge base some rules may be missing or indefinite. The missing or indefinite rules may indicate impossible range or not well-defined attributes or values. Usually fine-tuning is needed to make these situations clear. The available operations of the rule set are the same then in rule-based knowledge bases.

The Reasoning

Reasoning in case-based rule system works and looks the same as in rule-based systems (see chapter Original Decision – The Reasoning, though without fine-tuning the evaluation of a new case(s) may be indefinite or none at all. In this second situation it is strongly recommended to repeat the Case-Based Reasoning with the new case(s) included.

Tacit Knowledge and Fine-Tuning

The missing or indefinite rules may be made definite by simply changing the outcomes of the rules manually. However, it is worth consideration, what caused these missing or indefinite rules? If the expert is sure, that it indicates an impossible range, the rule may remain missing or indefinite; if there is a new case(s) falling into that range, perhaps the conditions of the reasoning are changed, thus the refreshment of the Case-Based Reasoning should be considered. If during the fine-tuning of the reduced knowledge base implied changes of attributes and/or values, these changes should be applied to the case-based knowledge base as well, and the Case-Based Reasoning should be repeated. As the hierarchy of attributes in the reduced knowledge base is single-levelled, it can easily happen that there are more then 3-4 attributes, which makes handling of the rule set difficult. Fine tuning the

Case-Based Rule Graph and using it as feedback to the original rule-based or casebased knowledge base the tacit knowledge is pulled to explicit domain.