Designing knowledge-based systems to facilitate innovation: three cases from practice

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Introduction

Although having much to offer to each other, the disciplines of innovation and knowledge management hardly share the same path. The role of knowledge in innovation has been recognised in knowledge management literature (e.g. McElroy, 2003; Nonaka & Takeuchi, 1995). This role is particularly explained in relation to the central position the process of problem solving takes within innovation processes; humans participating in innovation processes constantly solve problems in order to realise the intended innovation objective (Nonaka and Takeuchi, 1995).

From the perspective of innovation, however, the role of knowledge is hardly made explicit. Brown & Eisenhardt (1995) discuss three streams within innovation research. These focus on respectively rationality - innovation as the result of rational planning - , communication – innovation as the result of social interaction -, and disciplined problem solving – innovation as the result of problem solving. Although these streams can be explained in terms of knowledge, this is not explicitly done. If knowledge indeed plays such a central role in innovation processes, we argue that innovation processes would benefit from the insights, methods, and technologies that are available from the field of knowledge management. Especially the use of knowledge based systems, such as for instance decision support systems, we argue can benefit innovation processes.

Generally, innovation is characterised by the two elements of novelty and problem solving. As indicated before, Nonaka et al. (1995) place knowledge development at the heart of innovation. They indicate that knowledge development is needed in order to solve the problems with which individuals within an organization are deliberately confronted with. West & Farr (1990) emphasize the element of novelty. They define innovation as the "intentional introduction and application within a role, group, or organization of ideas, processes, products, or procedures new to the relevant unit of adoption, desinged to significantly benefit the individual, the group, organization, or wider society" (West & Farr, 1990, p.9). The introduction of novelty indicates that individuals involved in innovation are required to change their habits and behaviours, in order to deal with the novelty and to benefit from it. These individuals realize this change of their habits and behaviours through problem solving processes, or in other words by actively dealing with the change incurred by the introduced novelty.

From a knowledge (management) perspective, behaviour is identified as the consequence of an individual's knowledge (Jorna, 2006). In other words, a change of behaviour requires that an individual changes his knowledge. Innovation brings about the necessity for an individual to change his current knowledge, thus abandoning old insights, and learning new. Knowledge management is the discipline that focuses on such processes of changing knowledge. Knowledge management interventions aim to manage knowledge of a specific social context or unit of adoption. Two lines of intervention exists: social and techno-structural (Alvesson & Kärreman, 2001). The former means knowledge management acts through social interaction. The latter means that knowledge management is realised by changing an individual's formal and / or technical environment. This article focuses on this latter line of intervention.

In this article we focus on designing knowledge-based systems to support innovation. To achieve this, we draw lessons from three case studies in which knowledge-based systems have been developed and applied within innovation contexts. We provide an answer to the questions what design factors should be considered when knowledge-based systems are developed for an innovation context, and how these need to be handled in order to make the knowledge-based system fit such contexts.

In section two, we explore the relation between innovation and knowledge management in more detail. We start by elaborating on innovation as a knowledge management problem. Next, we derive design factors of knowledge-based systems that need to be considered when developing such systems for innovation contexts from available theory. Section three covers three case studies. We start with a treatise of OPTIras™, a knowledge-based system for the starch potato industry. This application supports farmers in selecting a potato cultivar for the crops they intend to grow in the upcoming season. The next knowledge-based system is Optichem, which was designed to aid cleaners and truck drivers in assessing potential dangers involved with chemical substances they encounter when performing their tasks. The last knowledge-based system we discuss is , a simulation model for starch potato growth. This simulation model is used in two systems. The first aids starch potato farmers with growth management decisions, at operational and tactical levels. The second aids factory planners to estimate total potato production for the current growth season, in order to estimate the required factory capacity. We finish the paper with a reflection on the design factors that are important when developing knowledge-based systems for innovation contexts.

Theory

Innovation as a KM problem

Innovation, or the introduction of novelty in an existing context, implies that individuals within this context are confronted with unfamliair knowledge, which they need to acquire. We approach the context in which an innovation is realized as a task environment (Newell & Simon, 1972). A task environment is an environment that imposes limits on individuals' problem-solving activities, thus focussing their behaviours to achieve certain objectives (Faber, 2006). Innovation alters the task environment by introducing something new in it. Regarding the novelty that innovation introduces, individuals need to determine how they can utilize it to their benefit in their task environment. Individuals cope with innovation through problem solving and learning.

In problem-solving, individuals construct a mental model of the problem, seek alternative solutions, and choose a solution (Simon, 1960), using knowledge they hold in their minds. The mental model of a problem is referred to as a problem space (Newell and Simon, 1972). A problem space represents the problem an individual is faced with, in terms of knowledge elements. A knowledge element is a meaningful mental representation in a human's mind (Newell, 1982). A coherent set of knowledge elements comprise a knowledge domain. A problem space can involve knowledge elements from one or more knowledge domains. If an individual holds knowledge elements from a certain knowledge domain in his mind, this knowledge domain is said to be a familiar knowledge domain (Faber, 2006; Peters, 2006). Concerning a familiar knowledge domain, the construction of a problem space is relatively easy. Individuals use already gained insights and priorly acquired knowledge to build-up the problem space. Alternatives are then found relatively effortlessly, so is choosing a solution.

Novelty by definition indicates that individuals possess little knowledge about it. The novelty is not represented in the knowledge individuals already possess. Therefore, knowledge related to novelty is considered to be part of an unfamiliar knowledge domain. Because of a lack of knowledge relating to the novelty problem solving is hampered. When confronted with a novelty, construction of a problem space is more difficult, as are seeking alternative solutions and choosing a solution. The distinction between solving problems involving knowledge from a familiar knowledge domain and problem-solving in an innovation context has been explained as the distinction between problem-solving regarding well-structured and ill-structured problems (Simon, 1973). As indicated, individuals possess knowledge in case of well-structured problems and are able to solve these kind of problems. In order to utilize a novelty to their benefits, individuals need to acquire new knowledge that is largely unfamiliar to them; in order to solve ill-structured problems, they need to construct a problem space to represent the problem, plot alternative solutions, and choose a solution.

The concept of *knowledge crossover* expresses the situation in which an individual needs to acquire knowledge from an unfamiliar knowledge domain (Peters, Faber & Jorna, 2008). A special class of knowledge is expertise. An innovation might change a task environment such, that expertise is demanded from the individuals involved. Expertise is described as extensive, task specific knowledge acquired from training, reading and experience (Turban & Aronson, 2001) and as knowledge progressed beyond the levels of domain knowledge (Alexander, 1992). The acquisition of knowledge or expertise in case of ill-structured problems is costly, involving learning (Waern, 1989).

In a cognitive information processing approach, learning (i.e. knowledge construction) is described as the absorption of experiences and the (re)organizing of existing mental representations (Jorna, 1990). The characteristics of the information processing approach can be found in constructivist learning theory. Constructivism is a philosophical view on how we come to understand or know (Savery & Duffy, 2001). Savery and Duffy (2001) described three propositions to characterize this philosophical view. First, the notion that '[u]nderstanding is in our interactions with the environment' is a core concept of constructivism. Understanding is an individual construction, whereby an individual, the learner, constructs an understanding based on information that is transmitted to him from an external source or knowledge provider (e.g. another human being or written text). Since all individually constructions are different, it is not possible to share understandings. Instead, people can test the degree to which our individual understandings are compatible (Savery and Duffy, 2001). Second, a perturbation is a condition for cognitive change (Savery and Duffy, 2001; von Glaserfeld, 1989). Other terms for this perturbation are puzzlement or cognitive conflict and they can be seen as a goal for learning. The goal of the learner is central in considering what is learned (Savery and Duffy, 2001). And third, not all constructions are equally viable. The social environment is critical to the development of our individual knowledge; other individuals are the primary mechanism for testing our understanding (Savery and Duffy, 2001). These other individuals serve as the source of puzzlement that stimulates learning (von Glaserfeld, 1989).

According to constructivists learning theory, to learn an individual has to incrementally and actively assimilate and accommodate knowledge (Rajlich, 2003; Savery and Duffy, 2001; von Glaserfeld, 1989). The process of assimilation denotes that learners process new facts and fit them into the existing knowledge in the form of schema (i.e. knowledge representations). The construction of schema consists of three parts: (1) recognition of a certain situation ("recognize"), (2) association of a specific activity ("act") with the situation and (3) expectation of a certain result (von Glaserfeld, 1989, p.127). When the expectation has not been met (resulting in the generation of a perturbation), the learner has to reorganize ("act") his existing knowledge so that new schema can be constructed. This process is called accommodation (Rajlich, 2003; von Glaserfeld, 1989).

From this view on learning it is inferred that prior knowledge is an important factor in the learning process (Spiro et al., 1991). Next to constructivist theory, there is ample evidence for this statement in literature from other fields (McGuinness & Patel-Schneider, 1998; e.g.Waern, 1989). When information and facts from an information source (after several accommodation trials) still fit imperfectly into a user's set of prior knowledge, users modify the facts to make them fit. Moreover, when the difference between the individual's prior knowledge and the information provided by the source is too big no assimilation or accommodation will take place at all (i.e. all the new facts are rejected). When a user rejects or improperly modifies information no effective learning can take place, because critical information is altered incorrectly or thrown away (McGuinness and Patel-Schneider, 1998).

In the situation of innovation, individuals start the learning process, trying to acquire expertise from external sources. No accommodation and no assimilation will take place, when the knowledge levels of the source and the individual are too distant. This is exactly what takes place in situations of knowledge crossover: the individual learner lacks prior knowledge to deal with the innovation and is unable to understand knowledge or expertise from an unfamiliar domain. Consequently, when the required knowledge to deal with the innovation cannot be learnt, no effective and/or efficient problem-solving takes place. To prevent this from happening, knowledge should be translated and presented in an understandable manner. This is the main task of KM concerning the development and implementation of knowledge-based systems.

Knowledge-based systems in innovation contexts

In order for a knowledge-based system to be applied in innovation contexts, it should be able to deal with situations of knowledge crossover. The knowledge provider must consider the receiver's knowledge level (Carroll & McKendree, 1987; Waern, 1989). Regarding knowledge-based systems, the receiver is identified as user. To cope with a knowledge crossover a human or artificial knowledge source should try to present the knowledge in an understandable manner, adapted to the knowledge level of the user (i.e. mutual understanding). Here, we refer to *knowledge usability*: the effort required for a knowledge receiver to learn, understand and use knowledge presented by a knowledge-based system (Schreiber et al., 2002).

Little attention is given to knowledge usability in knowledge-based systems literature. Therefore design factors are not available and need to be developed to design effective and efficient knowledge-based systems dealing with a knowledge crossover. The design factors should contribute to knowledge usability. We consider design factors associated with knowledge usability as critical success factors for a knowledge-based system dealing with a knowledge crossover.

In innovation contexts, a knowledge-based system should function as a knowledge provider covering three functions. First, the knowledge-based system should be able to solve problems within the unfamiliar knowledge domain. In other words, it should provide a view on knowledge from a knowledge domain that is unfamiliar to its user. Second, the knowledge-based system should provide this view on the unfamiliar knowledge domain in such a fashion that the user understands the unfamiliar knowledge. Third, the knowledge-based system should provide this view on the unfamiliar knowledge domain such that the user is able to incorporate the unfamiliar knowledge in his problem-solving activities. We elaborate on these three functions.

The application of knowledge-based systems to provide a view on an unfamiliar domain is conceptualized by Waern (1989), in her framework of human-computer interaction. Figure 1 shows an adapted version of this framework. Waern's framework starts from the premise that introducing a knowledge-based system in a task context, results in a division of the task. A part of the original task, which used to be performed exclusively by a human individual, is moved to the knowledge-based system. A similar line of reasoning applies to introducing a knowledge-based system in a task environment to support innovation. Whereas a task is divided over knowledge-based system and human individual in the original framework, the knowledge-based system is assigned to the task-parts the innovation lays on the task environment. For instance, when regarding the introduction of an electronic calculator in financial departments as an innovation, the task-parts involving calculations that normally were executed by hand the electronic calculator now takes over. We denote these task-parts as innovation task. For a knowledge-based system to perform the innovation task correctly, it should be equipped with knowledge elements from the unfamiliar knowledge domain (Faber, 2006).

In relation to the ability to make unfamiliar knowledge understandable to its user, a knowledge-based system is considered to consist of two relevant levels: the task level and the knowledge level (Faber, 2006). At the task level the interaction between the knowledge-based system task and the user task is facilitated. At the knowledge level the domain knowledge resides that is used in the task. For innovation contexts, the knowledge-based system should contain knowledge from the unfamiliar domain at the knowledge level, and perform the innovation task. Additionally, the knowledge-based system needs to have knowledge about its user at the knowledge level. Waern (1989) identifies this as 'model of user', which is a representation of the user within the knowledge level of the knowledge-based system. This model of user contains knowledge elements from the user's familiar knowledge domain. In this fashion, the model of user enables the knowledge-based system to translate knowledge from the unfamiliar knowledge domain to terms that connect to the knowledge elements with which the user is familiar.

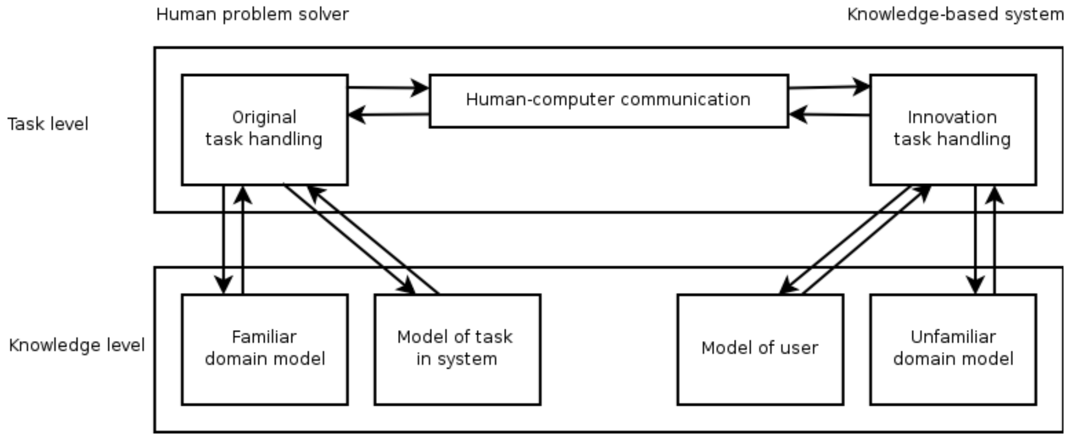

Figure 1 Task and knowledge levels in human-computer interaction (inspired on Waern, 1989)

In addition to being able to translate unfamiliar knowledge elements into familiar ones, the knowledge-based system should enable its user to incorporate these knowledge elements into the user's problem-solving activities. This connection is made at the task level. At the task-level, the knowledge-based system (i) executes its innovation task and (ii) facilitates interaction with its user. The interaction between user and knowledge-based system is realized through the interaction by the 'human-computer communication' component in Figure 1. Through the interaction component, the user is able to co-ordinate his own task with the innovation task performed by the knowledge-based system and vice versa. Additional to containing knowledge elements from the user's familiar domain at the knowledge level, knowledge about the user's task is incorporated in the knowledge-based system at the task level within the 'human-computer communication' and 'meta-communication' components.

We argue that in order for a knowledge-based system to support humans in innovation contexts, the interaction between knowledge-based system and its user need to be shaped such that knowledge-crossover is taken into account. For this, the knowledge-based system needs to be equipped with a means to bridge the distance between the user's familiar and unfamiliar knowledge domains. As we indicated before, this distance needs to be bridged in terms of understanding and in terms of incorporating unfamiliar knowledge elements in the user's problem-solving process. In the next section, we present three cases. In these cases, three situations are sketched. Each situation reflects the three aspects of (i) being an expert in the unfamiliar knowledge domain, (ii) translating the unfamiliar knowledge domain into familiar knowledge, and (iii) enabling the incorporation of unfamiliar knowledge elements in problem-solving activities are present in various degrees. The exact configuration of these aspects determines the successfulness of the respective knowledge-based system.

Cases

We present three case studies in which a knowledge-based system has been implemented as an aid in an innovation context. Each case involves a knowledge crossover, either between completely distinct knowledge domains or within one knowledge domain between a perspective from practice and a perspective from research. For each case, we discuss the innovation context in which we detail the situation of knowledge crossover. Also we discuss the general characteristics of the knowledge-based system that was build to support individuals to cope with this knowledge crossover. Next, we discuss the approach that was chosen towards realization of the knowledge-based system. Here, we plot the lines along which the knowledge-based system has been designed and implemented. Last, we discuss the consequences of the chose approach in relation to the success or failure of the application of the knowledge-based system in the specific context.

Case 1: OPTIras™

The OPTIras™ case study is situated in the Dutch starch potato industry, an industry that is currently faced with various societal, technological and climatological challenges. The most pressing challenge relates to changes in the EU's Common Agricultural Policy. This challenge concerns the stopping of current subsidies for potato starch production and the opening up of EU border to sources of starch from outside Europe. Technical challenges concern an increasing use of information, use of biotechnology and increase in farming scale. Climatological challenges are changing precipitation patters, more frequent periods of extreme weather, and a rise of average temperatures. These challenges together affect the farming context and cause fluctuations in farmer income (Faber, 2006). The survival of the starch potato industry depends on the ways individual farmers deal with these challenges.

Looking ahead, the Dutch starch potato industry has participated in research into the mentioned challenges in the Agrobiokon (Agro-Biotechnological Carbohydrate Research Netherlands) research programme. This research programme's objectives are (i) the reduction of production costs and crop losses, (ii) the increase of yield through increasing production per hectare within the limits of the available environment, natural, and societal resources, and (iii) the development of new starch products and processes with high added values (Jorna, 2006). To achieve these objectives, various studies have been executed within the Agrobiokon research programme aiming at the various stages of the starch potato value chain from crop growth through processing industry to consumer. This case study is situated at the beginning of this value chain, at the stage of potato production. In this stage, the Agrobiokon programme initiated studies focusing on the fundamentals of crop growth. Additionally, it initiated various projects aiming to communicate these scientific findings of these studies to farmers to be applied in practice.

Studies into crop growth fundamentals laid bare a plethora of problems farmers need to overcome with in short term in order to safe-guard their survival. The five most important problems are (i) nematode infestation, (ii) storage losses due to harvest damage, (iii) viruses, (iv) storage loss due to rot, and (v) storage losses due to inappropriate storing techniques. Eighty percent of Dutch starch potato farms would sustain if these problems are properly handled, increasing their average incomes by €500 per hectare per year. OPTIras™ supports farmers to resolve the problem of nematode infestation, particularly the Potato Cyst Nematode (PCN) (Jorna, 2006).

OPTIras™ is a knowledge-based system for cultivar selection that supports a farmer in selecting cultivars relative to cultivar characteristics. A variety of properties relating to yield, resistance against pests and diseases, and storage, characterizes a potato cultivar. Personal preference, diseases present in the farmer's field and cultivar properties determine the farmer's choice. OPTIras™ assists the farmer in choosing the cultivar properties and sorting the cultivars based on priorities. Despite its long history and the fact that a lot is known about it, PCN still costs an average of €150 per hectare per year in the starch potato industry. This is about 10-15% of a farmer's net income. Reducing the infestation to economically acceptable levels requires the right combination of cultivar, growth frequency, field choice and nematicide usage. Cultivars differ greatly with regard to resistance (the ability to reduce the infestation) and tolerance (the ability to withstand the infestation), two uncorrelated cultivar characteristics. A non-resistant and highly tolerant cultivar can multiply the existing nematode population by 30 times during a growth season, while a highly resistant and intolerant cultivar reduces the population by two to three times. However, the intolerance indicates that the crop is highly affected by the nematode population, resulting in high losses of yield.

The OPTIras™ knowledge-based system aids farmer's in cultivar selection, as a way to manage PCN infestation and crop loss caused by this infestation. To fulfil its role, OPTIras™ combines information about available cultivars with the population dynamics of the nematode and the properties of available pesticides. The combination of the various pieces of information of cultivar, nematode, and pesticide is realized making use of an optimization model. Scientific insights gained in the Agrobiokon studies into the fundamentals of crop growth form the basis of this optimization model. In order to let a farmer interact with the optimization model, OPTIras™ consists of five pages: 'Field identification', 'PCN history', 'Reorder Cultivars', 'Yield information', and 'Crop rotations'. On the 'Field identification' page the farmer submits information concerning his field. This concerns the type soil (peat or sand), and the yield he desires his field. On the 'PCN history' page, the farmer specifies the PCN infestation level of his field. The 'Reorder cultivars' page enables the farmer to specify his preferences regarding various aspects of a cultivar (e.g. PCN tolerance and resistance, potential starch production, etc.). The pages 'Yield information' (see Figure 2) and 'Crop rotations' provide the outcome of the optimization model to the farmer regarding the effect of cultivar selection on respectively current year's crop and on the crop growth in the upcoming 5 rotations. OPTIras™ ensures that the farmer gains insight into nematode damage levels and the financial consequences of a wrongly selected cultivar or incorrect application of pesticides. In this fashion, OPTIras™ contributes to sustainable soil management.

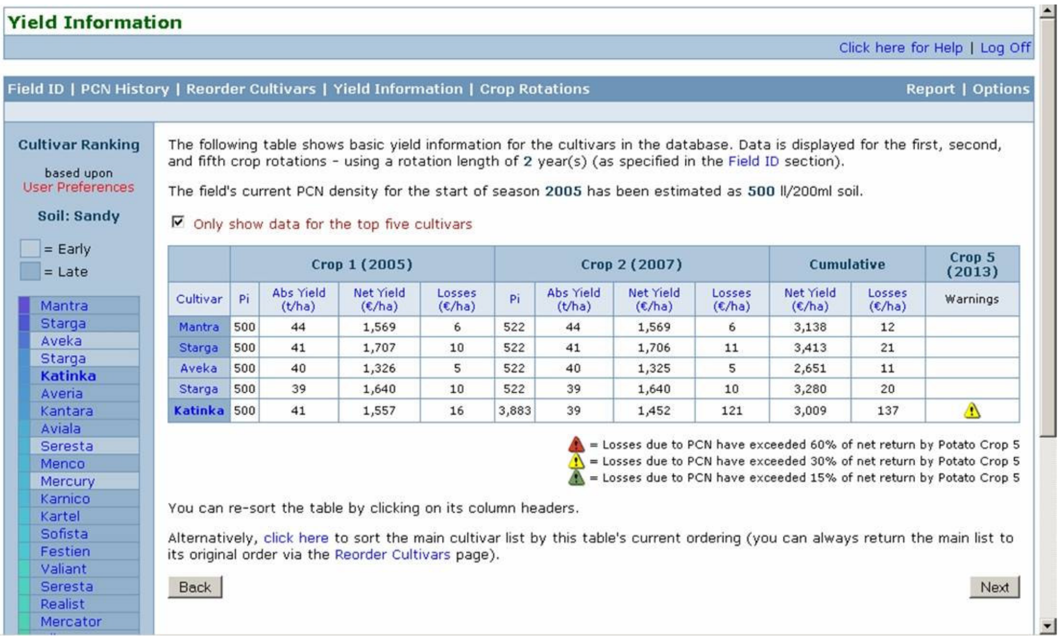

Figure 2 OPTIras™: yield information page

The knowledge crossover in the OPTIras™ case concerns the transfer of knowledge from scientific research on PCN dynamics and the effect of cultivar selection to farming practice. Although this scientific and practical knowledge lie within the same knowledge domain, they reside at opposite ends. Scientists have a formal view on PCN dynamics and crop growth. They use mathematical equations to express the ways a PCN population develops and the effect a potato cultivar has on this PCN population (resistance). The effect of a certain PCN infestation on crop growth (tolerance) is similarly expressed in formal language. Farmers use a practical approach to the relations between PCN infestation and crop growth. In a 2005 study into the use of information sources within the Dutch starch potato industry, Faber (2006) found that farmers have different ideas about cultivar selection than scientists. Farmers are less clear about the factors that are important in cultivar selection in relation to PCN management and yield. Additionally, the same study shows little variation in cultivar selection among farmers. Most farmers choose from a set of three different cultivars. One interpretation might be that farmers are less concerned with cultivar selection, due to a lack of insight into the effect of cultivars on the PCN population in their field. Another interpretation might be that farmers are less concerned about PCN infestation and the negative effects this has on their crops, but are much more concerned about the time and effort they need to invest in growing a specific cultivar. This latter interpretation is an indication that farmers are more likely to choose the cultivar that is easiest to grow.

In terms of Figure 1, the OPTIras™ knowledge-based system has been realised, focusing strongly on the right-hand side of the schema. Expert domain knowledge of the unfamiliar domain of cultivar selection has been implemented in the system. The choice to incorporate this expert knowledge equips the knowledge-based system with the expertise to execute its designated innovation task within the cultivar selection knowledge domain. However, OPTIras™ lacks an internal 'model of user'. In other words, OPTIras™ has not been equipped with any knowledge about its user, disabling the system to translate unfamiliar knowledge elements about cultivar selection into the practical, familiar knowledge domain of farmers. Additionally, OPTIras™ provides little footholds that allow farmers to incorporate the innovation task (improving cultivar selection) OPTIras™ performs in their problem-solving activities. OPTIras™ strictly follows the flow of the underlying optimization model, instead of connecting to the flow of the problem-solving activities of the farmer regarding cultivar selection.

In summary, OPTIras™ has been developed with a strong orientation towards expert knowledge. The user of the knowledge-based system has been disregarded. The result is a system that is able to reason as an expert within the unfamiliar knowledge domain of cultivar selection. However, OPTIras™ is unable to connect expert insights to the knowledge elements of its users, let alone to their problem-solving activities. The disregarding of users has made the knowledge crossover, OPTIras™ intended to achieve, as unsuccessful.

Case 2: Optichem

The Optichem case study describes an innovation context in the Dutch paper industry, centring on chemical substances that are used in paper production. The use of chemicals affects various tasks among which paper production, cleaning, and transporting. The Optichem case study involves the cleaning and transporting tasks of industrial cleaners and truck drivers.

Paper production is a fairly simple process, consisting of seven production stages. In the first stage, wood is grinded into small fibres. Next, the fibres are bleached to ensure the paper's white colour. The third stage adds water to the bleached fibres, and transforms the fibres into paper pulp. This paper pulp is subsequently sorted and diluted in the fourth stage. In stage five, paper sheets are formed, by dividing the paper pulp on a sieve. The formed sheets are subsequently pressed in stage six and thermally dried in the last stage. Over the last decades, the use of chemicals in paper production has increased. At various point in the seven production stages, chemicals are added to set a specific characteristic of the end product. For instance, bleach is added in the second stage to whiten the paper. Or, specific chemicals are added in the sheet forming and pressing stages to fixate the paper's surface to improve its writeability or to give it a glossy finish.

The introduction of chemicals in paper production is the innovation in the Optichem case. Although chemicals have been introduced and applied in paper production, workers who perform various tasks at a paper mill site do not possess knowledge to handle these. Schooling and training programmes for these workers have not been altered to equip them with any knowledge about chemicals. A general lack of knowledge about chemicals at various people, who perform tasks at paper mill sites, has resulted in a number of problems relating to personal and environmental safety. Because of their lack of knowledge, workers are not able to predict the danger involved with the chemicals they encounter when performing their tasks.

Optichem is a knowledge-based system prototype that has been designed to aid various workers at a paper mill site to cope with chemical substances they encounter when performing their tasks. The case study described here focuses on the tasks of industrial cleaners who clean paper machines and of truck drivers making a delivery of chemicals at a paper mill site. Chemicals used in paper production are stored at various places on a paper mill site and present in the various machines used to produce paper. This presence of chemicals affects the task environments of cleaners and truck drivers. Cleaners having to clean paper production machines are in direct contact with the surfaces that during operating hours carry paper and chemicals. It is the cleaner's job to clean these surfaces. Although paper machines are not operational during cleaning, residue from the last production runs still are present in these machines. Next to cleaners, truck drivers who make deliveries at paper mill sites, not only are confronted with their chemical cargo. They too face other chemicals at the unloading facility of a paper mill site. Knowledge about which chemicals are present and how to use the unloading facility is of the essence for the truck driver to ensure safe unloading of his cargo.

The Optichem knowledge-based system prototype aids truck drivers and cleaners in assessing their current situation regarding the chemicals they encounter in their task environment, regarding personal safety. Additionally, Optichem advices its user about measures they need to take in order to protect them from harm. The reasoning mechanism of Optichem is realized using the Algernon rule-base (Hewett, 2004). The rule-base has been filled with rules describing chemical reactions between substances, and rules that indicate what safety measures need to be taken when a chemical reaction takes place.

In shaping the communication with its user, the Optichem user-interface has been designed closely regarding the knowledge level of truck drivers and cleaners regarding chemical knowledge. Two different user-interfaces have been developed on top of the rule-based engine. The first interface uses a wizard-structure to let users interact with the chemical domain. The second user interface groups all relevant knowledge elements within one screen and lets the user directly manipulate various settings regarding chemicals and conditions in which these chemicals are encountered.

Figure 3 shows the first interface that has been developed for the Optichem knowledge-based system. This interface guides its user through the chemical knowledge domain in nine steps. First the user indicates which task he is performing; the current prototype allows the selection of the unloading and cleaning tasks. Next, the user indicates at which paper mill he performs his task. In this way, Optichem is able to respond to location specific situations. In the following screen, the user indicates the supplier of the chemical substance the user has encountered. Taking into account the supplier of the chemical substance, enables Optichem to cope with variations in composition of a chemical substance between suppliers. The fourth screen asks the user to specify the chemical substance he is confronted with (top-left window in Figure 3). In the fifth screen the user is informed about possible dangers, and the sixth screen indicates which countermeasures and precautions the user can take to limit these dangers (bottom-left in Figure 3). Screen seven is similar to screen three: the user can select a second chemical substance he encounters. By selecting a second chemical substance, the user lets Optichem know that he is interested in the possible reactions that can occur when the two chemicals are mixed. The user is informed about the possible dangers, and the countermeasures and precautions he can take in screens eight (right screen in Figure 3) and nine. The nine steps from the wizard-structured interface are grouped in one screen in the second user interface of Optichem (see Figure 4).

The rationale behind developing two distinct interfaces for the Optichem knowledge-based system has been to facilitate accommodation and assimilation of the cognitive system of its user as much as possible. Whereas the wizard-structured interface guides its user through the chemical knowledge domain step by step, the single-screen interface confronts its user with all peculiarities of this domain. These two interfaces were used in an experiment with cleaners and truck drivers to determine which kind of communication is most fitting to communicate chemical knowledge to truck drivers and cleaners. Users using the wizard-structured interface are slightly better able to understand the information that is presented about the chemical knowledge domain by Optichem (Peters, Faber, and Jorna, 2008).

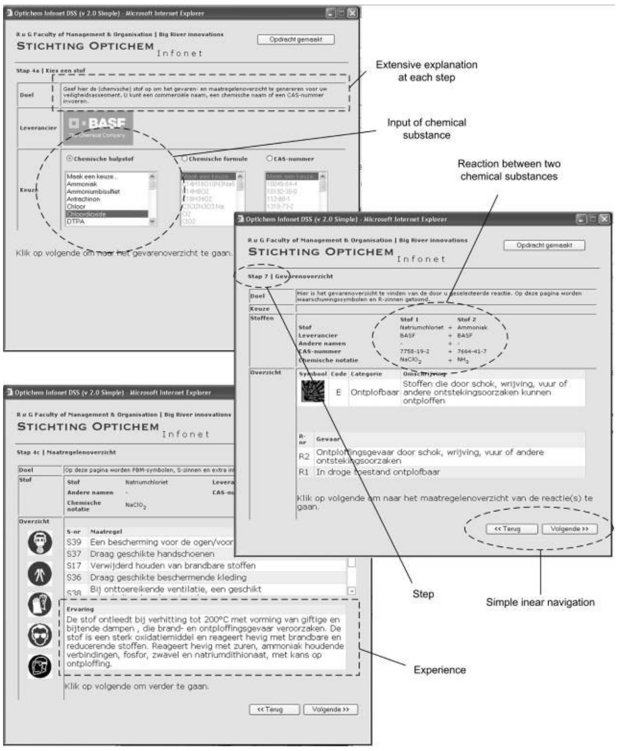

Figure 3 Optichem: wizard-structured interface

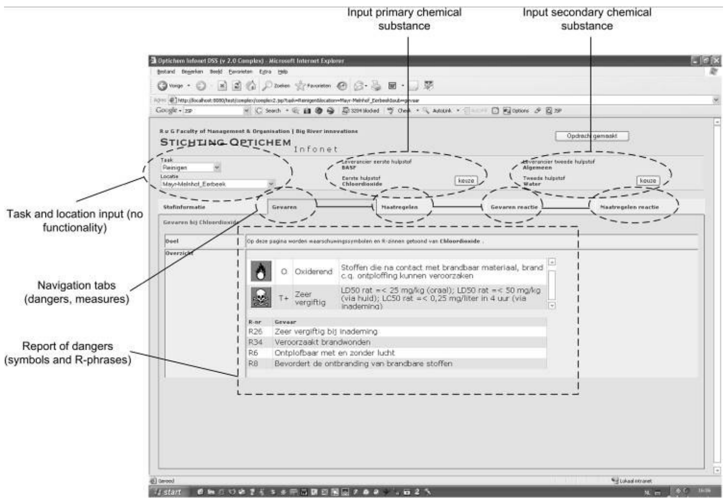

Figure 4 Optichem: single-screen interface

The knowledge crossover in the Optichem case involves the knowledge domains of chemicals and the knowledge domains truck drivers and cleaners have knowledge about. In the context of a paper mill site, truck drivers and cleaners are lost regarding the chemical knowledge domain. In the pre-test stage of the experiment reported by Peters et al. (2008), users were tested for their prior knowledge regarding the chemical knowledge domain. They were asked to complete an exercise that closely resembles a situation these users encounter in reality. None of the users showed to possess sufficient knowledge to complete this test. Therefore, the chemical knowledge domain is considered to stand apart from the knowledge possessed by truck drivers and cleaners.

The Optichem knowledge-based system has been developed to bridge the gap between the chemical knowledge domain and the knowledge domains from which truck drivers and cleaners possess. The development of the system concentrated strongly on the configuration of the interaction between user and system. In terms of Figure 1, the top-half has been the main focus of the Optichem knowledge-based system. Because of lack of chemical expertise during the development and construction of the system, the rule-base of the Optichem system contains little knowledge about the chemical knowledge domain. The knowledge that is present however is communicated in an understandable fashion to Optichem users. Also, the current arrangement of the Optichem user-interface facilitates the connection between the innovation task and the task of truck-drivers and cleaners adequately.

Summarizing, the Optichem knowledge-based system has been developed with a careful consideration of its intended users. As a result, Optichem is capable of translating the unfamiliar knowledge domain of chemicals to truck drivers and cleaners. Due to a lack of chemical expertise during development, the Optichem rule-base does not provide real expert knowledge about chemicals, possible reactions, involved dangers, and countermeasures or precautions users can take. The focus on the user also enables Optichem to connect closely to the problem-solving activities of its users. Whereas the user-focus positions Optichem favourably in the problem-solving activities of truck drivers and cleaners with regards to chemical knowledge, the lack of thorough expert knowledge makes the system unsuccessful to provide practical support in a real situation.

Case 3: TIPSTAR™

This case also is situated in the Dutch starch potato industry. Whereas the OPTIras™ knowledge-based system focuses on cultivar selection, the TIPSTAR™ knowledge-based system supports farmers during the growth season, from the moment potatoes are planted until they are harvested and driven to the factories to be processed into starch. Additionally, TIPSTAR™ aids factory planners to make a prognosis of the total production of starch potatoes that will be delivered to the processing factory in a season by member farmers. While OPTIras™ contributes to the Agrobiokon objective of reduction of production costs and losses, TIPSTAR™ also focuses on the objective to increase yields by increasing production per hectare within the limits of the available environment, natural, and societal resources.

The TIPSTAR™ knowledge-based system discussed here consists of two separately developed modules, the TIPSTAR™ simulation model and the TIPSTAR™ user-interface. We discuss them both. The TIPSTARTM™ simulation model has been developed as a scientific simulation model of potato plant growth. The model is based on the paradigms and concepts of system theory. The crop, soil, and climate are identified as the subsystems to be studied and understood, and that can be described using mathematical functions. Knowledge from the domains of soil-physics, soil-chemistry, crop ecology, eco-physiology, and meteorology are incorporated in the model. The idea was that if this knowledge is applied in practice, an improvement of the sustainability of starch potato growth can be realised. The simulation model formalises this knowledge, in which crop management, daily weather, physical, and chemical soil data are inputs to the system.

Solar energy, temperature, water, fertilisation, and diseases and plagues determine growth and development of starch potatoes. The crop growth model assumes that solar energy transforms into assimilates (sugars), and subsequently divides among the processes of growth, maintenance, and reproduction. These processes function well if enough nitrogen and water are present to produce protein and other structure and stock components. The plant absorbs nitrogen through its roots, after which nitrogen is transported towards the different organs for processes of bio-synthesis. Water is required for uptake of nitrogen, for breathing and cooling of the plant. The mentioned processes describe growth and development of the different organs of the plant: leaves, stems, roots, and tubers. Technically, this is called a `multi-compartment stochio-metric dynamic crop growth model'.

The soil-water system simulates the crop's daily availability of water. The farmer's irrigation data is used together with precipitation data from weather stations and groundwater data from the 1:50,000 territorial map of The Netherlands. The soil is divided into 1 centimetre thick layers. The functional description of these layers is aggregated into soil profiles of 1.20 depths. In this manner, water retention can be determined per layer of the soil profile. The simulation calculates the available water per 1 cm layer, using the difference between the soil's drainage and its capillarity. The crop growth model calculates total root depth and root density per 1 centimetre layer; summing up to the total water usage of the crop.

The Soil-Organic Substance and Nitrogen system simulates the crop's daily availability of nutrients (nitrogen) for each separate layer of the soil. In this, the farmer's fertilising data are used. The soil is schematised similar to the soil-water model. The crop's daily available amount of nitrogen per layer results from the processes of mineralisation, nitrification, de-nitrification, and drainage and uptake by the crop. Mineralisation is the process that transforms organic substance (such as green fertiliser, compost, or crop residue) into carbon dioxide and nitrogen (ammonium / nitrate). Herewith, mineralisation is one of the most important processes determining the soil's sustainability. The amount of organic substance of the soil determines its water retention, and is the source of the saprophytic soil life.

As indicated before, the TIPSTARTM™ simulation model has been developed from a scientific standpoint, building the model as generic as possible, refraining from incorporating context specific issues. Issues related to crop growth have been standardised. The model simulates plant behaviour in one point, which is used to estimate the behaviour of plants growing on one hectare. In other words, TIPSTARTM™ reduces everything relating to starch potato growth to simple units. Practical situations, as are encountered by farmers or other actors from the starch potato value chain, however are more complicated.

In order to make the TIPSTAR™ simulation model applicable to farmers, two separate user-interfaces have been developed that connect the scientific knowledge about plant growth to the practical situation of farmers and of factory capacity planning. The user-interface for farmers connects the TIPSTAR™ simulation model to their task of crop growth management. Figure 5 shows a screenshot of this TIPSTAR™ user interface, displaying simulation results to its user. The crop growth management task concerns activities regarding crop growth, stretching from pre-growth ploughing, to in-growth irrigation and fertilization, to harvesting at the end of the growth. TIPSTAR™ can support this task at operational (day-to-day management advice), tactical (investigating the consequences of alternative management strategies for a historic growth), and strategic (comparing management strategies and effects on soil composition for multiple growths regarding multiple years) levels. The current configuration of the user interface provides tactical support. It enables a user to define his fields, type of crops, location, soil composition, weather data/forecasts and other ecological and geographical data; it enables the creation of a virtual copy of a farmer's field. From this point on, the user interface handles the input of operations on the field, like sowing, ploughing, fertilizing, irrigating, etc. These operations can be actual operations, planned operations or experimental operations, depending on the objective of the usage of TIPSTAR™. For instance, during a training course an improved irrigation method can be explained by the results of TIPSTAR™ or during the season, a farmer can predict the effect of a planned increase in compost depending on different weather scenarios. The user interface has been designed to match the farmer's perception and knowledge of his domain and environment as closely as possible.

TIPSTAR™ support factory capacity planners regarding their planning task. Capacity planning concerns the construction of a production schedule for the processing of the total yield of all farmers in the region that is served by the planner's factory. This schedule concerns factory machines and employees. The factory capacity planner requires a forecast of the expected starch potato yield in order to make the schedule. Thus far, a forecast was made using several field samples during the growth, which is costly and time-consuming, and often leads to unreliable forecasts. The prognosis user interface provides the factory capacity planner a portal to the TIPSTAR™ simulation model. Figure 6 presents a screenshot of the results of a prognosis as displayed to the capacity planner. In configuration of using the TIPSTAR™ simulation model, the starch potato region is considered as one giant field consisting of the region's complete soil data. The user interface has been designed to handle the input of parameters, like crop emergence dates and weather data, and the result of the simulation: the forecast. The forecast is presented in management summary and graphical charts.

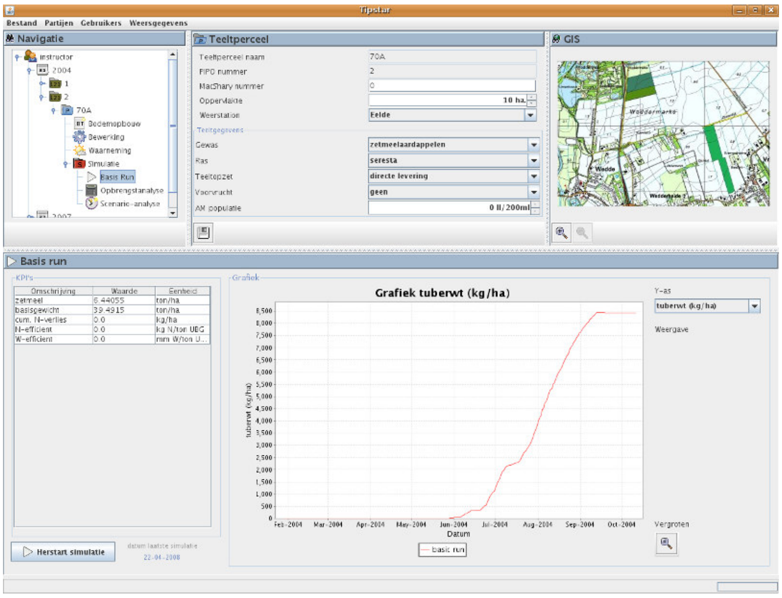

Figure 5 TIPSTAR™: output of simulation results

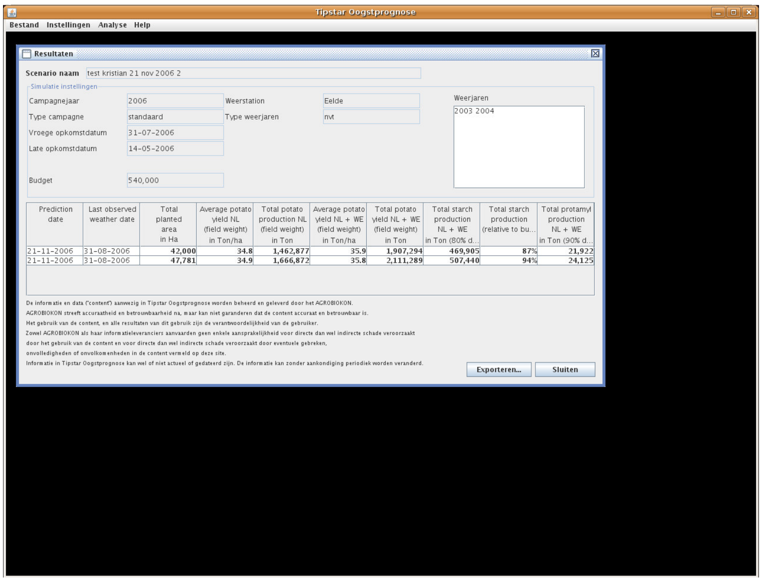

Figure 6 Yield prognosis: output of prognosis results

This case study concentrates on two knowledge crossovers, from expert knowledge about the knowledge domain of potato growth to one farming practice, and second capacity planning for starch processing factories. Because farmers are generally successful in growing crops, it is assumed they posses extensive knowledge about potato growth, possibly lacking few details that are incorporated in the TIPSTAR^{TM} simulation model. TIPSTAR^{TM} does not assist farmers in growing crops, but moreover it helps them to optimize their crop management. In contrast, capacity planners are unfamiliar with the potato growth knowledge domain. To them, TIPSTAR^{TM} intends to properly bridge the gap between the knowledge domain of potato growth and the domain of capacity planning.

Currently, no formal user-tests have been conducted on how TIPSTAR^{TM} functions when used by farmers. However, at several occasions we have had farmers using TIPSTAR^{TM}. They indicated that although the system is complex, and many data have to be inserted to make the simulation work, the system is understandable. The view TIPSTAR^{TM} provides on the expert knowledge of crop growth connects to the understanding farmers have of the knowledge domain. In the future, we plan to conduct various experiments involving farmers in order to get more insight into the appropriateness of design choices regarding TIPSTAR^{TM}'s user-interface and simulation model. From the initial reactions received, we expect TIPSTAR^{TM} to achieve the intended knowledge crossover.

Conclusion

This article started from the idea that innovation and knowledge management are two disciplines that can benefit from each other. Especially the application of knowledge-based systems was suggested to facilitate the introduction of something new in a social context. Individuals comprising this social context need to be assisted in dealing with the knowledge crossover the novelty lays upon them.

Knowledge crossovers can be bridged using knowledge-based systems, if both the unfamiliar and the familiar knowledge domains of the intended user are considered already from early design. Unfamiliar knowledge needs to form the core of the knowledge-based system. The system needs to be able to reason within the unfamiliar knowledge domain as if it were an expert. Familiar knowledge should be incorporated in the knowledge-based system to be able to communicate with the user that it supports. The knowledge-based system needs to provide a view on the unfamiliar domain, translating it into familiar knowledge elements and connecting it to the user's problem-solving activities.

The three case studies illustrate that a focus on exclusively the unfamiliar or familiar knowledge domain, does not result in knowledge-based system support of innovation. First signals indicate that the TIPSTAR^{TM} case has the potential of bridging the knowledge crossover from the expert side of the potato growth knowledge domain to the practical side. Future research is needed to further support this indication.

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