

Expert Recommender Systems in Practice: Evaluating Semi-automatic Profile Generation

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ABSTRACT

Expert recommender systems (ERS) are considered a promising technology in knowledge management. However, there are very few studies which evaluated their appropriation in practice. In this paper, we present results of a case study of expert recommender technology in a large European industrial association. Unlike existing expert recommender approaches, the system involves users in selecting textual documents for semi-automatic profile generation. Our study focuses on the appropriation of this functionality and discusses impacts from an organizational perspective.

Author Keywords

Expertise Recommender System, Knowledge Management, Second Wave

ACM Classification Keywords

J.4 [Social and Behavioral Science]: Sociology

INTRODUCTION

The concept of knowledge management (KM) has been the subject of controversial discussions during the past years. The CSCW community has criticized repository approaches to KM which assume that knowledge could be easily externalized and re-appropriated (e.g. [4, 2]). Taking the often implicit and social nature of human knowledge into account [20, 28], a second wave of KM applications has been postulated [6, 11]. Second wave KM applications support knowledge sharing and social networks among human actors – those who seek for certain knowledge and those who may possess it [2, 12, 30].

There are different KM applications which support human actors in finding, communicating, or cooperating with

experts on knowledge intense activities. While expert recommender systems (ERS) allow finding appropriate knowledge carriers based on their expertise profile, member or topic centered communication spaces encourage exchanging ideas or finding solutions to problems [12]. The design of these systems transcends the limitations of repository approaches. However, a profound set of evaluation studies is still missing, which look into specific design principles and their effects on practices of knowledge sharing in organizations.

Looking at ERS, one of the biggest design challenges is how to allow users to build expertise profiles quickly and reliably with as little manual efforts as possible yet also respect individuals' privacy. These conflicting requirements have led to the design of systems which emphasize speed of building profiles over privacy by collecting all or most of the information through some form of data mining [8, 15], or yellow-page systems which emphasize privacy over speed by asking the users to input the information manually. The ERS application discussed in this paper takes a novel position in this regard by combining self-reported directory information with keyword mining from users' personal files and folders, with permission.

To evaluate the viability of such a design approach the subtle interplay of technological and organizational factors needs to be taken into account. Therefore, the paper presents the results of an evaluation study of the ERS application within a major European national industrial association, called NIA for the purpose of this paper. The study was conducted over a period of eight months. Our study focuses on the system's performance in profiling users' expertise, benefits provided to users in their daily work practices and organizational impacts.

In the following sections, we will first survey the state of the art on existing ERS and related case studies. We then describe our research approach as well as the application design based on a requirements analysis at NIA. Afterwards the results of our evaluative study are presented in detail. We conclude by discussing our findings.

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STATE OF THE ART

While the CSCW community has come up with a variety of interesting design concepts for second wave KM applications [1, 3], there are considerably fewer studies which evaluate their impact on knowledge intense processes in organizations [5, 24]. In this paper, we will focus on expert recommender systems (ERS). These applications allow entering a search query for knowledgeable human actors and display an output list of potential experts. The search queries are matched against a corpus of personal data which indicates a human actor's expertise or interest. Most of these systems access personal data automatically in order to create and maintain user profiles without bothering the users. Besides expertise location, these systems can be used to generate competence profiles of (parts of) the organization or to identify competence gaps [14].

There is a large variety of technical implementations for expert recommender systems [8, 9, 13, 15, 16, 19, 25, 27]. Some implementations are based on text matching algorithms drawing on corpora such as textual documents, e-mails or chat messages [25, 9]. Other implementations regard more structured data, such as program code, scientific references or social networks to be appropriate indicators of expertise location [13, 17, 27]. Recent approaches allow matching different sources of personal data [8, 22].

While the diversity of technological approaches has widened considerably, only a rather limited number of studies has derived requirements for ERS or evaluated ERS technology in native organizational environments.

McDonald [17] and Groth & Bowers [10] provide empirical grounding for the design of ERS. In each of the case studies a real world organization, a medical software development company and a technical consultancy, are investigated in depth in terms of their expert finding practices and implications for technical design. The authors come up with contradictive conclusions with regard to the basic design principle of ERS. Groth & Bowers [10] argue against the traditional design approach towards ERS due to the situatedness of expert finding behaviour. To advance our knowledge with regard to this dispute, we need studies which evaluate different design principles of ERS.

McDonald [17] evaluates his ERS in a medical software company. The ERS finds developers most knowledgeable with regard to certain software modules based on a corresponding documentation in the source code. The study indicates that the expertise profiling worked satisfactory within the medical software company. Interestingly, additional applications of the ERS were suggested by participants during the evaluation study: The ERS could be used for the assignment of programming jobs or for a long term competence management. Lindgren et al. [14] found that the automatic profiling of their system (based on the users' individual configurations of search agents to the

internal DMS) did not work satisfactory because the user profiles were judged to be incomplete. The authors suggest using documents or e-mails from the users' working context for profiling. Moreover, it turned out that the ERS did not significantly improve social interconnectedness among the actors.

Ehrlich et al. [8] have built an ERS which analyses the content of outgoing e-mails and chats. Moreover, it takes the structure of the message exchange to construct a social network among the users. The system was deployed via an intranet site within IBM. Its pattern of adoption was evaluated by means of 11 phone interviews and log file analysis. Moreover, the authors were interested in the perception of their privacy mechanisms [8]. An additional study focused on the selection criteria for experts in the output list [23]. While the work within IBM offers interesting insights into the dynamics of the adoption process, it still lacks a long term perspective on the appropriation process and deeper analysis of changes in expert finding behavior.

The question arises whether ERS can overcome adverse conditions (lacking willingness for cooperation, time pressure) that can be found in many organizations and successfully introduce KM to these organizations. Different authors predict considerable improvements as a result of an increased mutual awareness of competences, skills and recent activities of human actors in organizations. However, up to now empirical evaluations on successfully applied ERS in organizations are rather sparse.

Even with regard to technical design principles, we lack evaluation data. Important design issues are still not answered in a satisfactory manner, especially how to identify corpora of personal data which are indicative of an actor, how to keep it up to date over time, or how to balance between the completeness of a corpora and privacy concerns. Regarding existing technical approaches to ERS, it is striking that none of the systems allows users to select or control the data for automatic profile creation. We assume that this is an important issue in terms of the users' privacy concerns as well as of an accurate and comprehensive expertise profile. The ERS rolled out in our study provides these features.

METHODS AND FIELD OF APPLICATION

The evaluation study was the final step in a three year lasting research project within NIA. For more details on requirements analysis and system development we refer to [21, 22].

NIA is one of the largest industrial associations in Europe. The association offers services such as networking among its member companies and information about market opportunities, legal regulations, sector-specific standardizations, or industrial property rights. Moreover, it offers technical or professional support and lobbying services at governmental institutions on behalf of its members.

NIA serves 3000 member companies from different branches of the machine tool and the capital goods industries. It consists of 37 sector specific vertical departments (sections) each dedicated to companies from specific industry sectors such as ‘agricultural machinery’, ‘pumps and systems’, or ‘software’. Moreover, it consists of horizontal units with cross cutting responsibilities (general departments), e.g. ‘business administration’, ‘law’, or ‘taxes’. In addition, NIA hosts several spin offs and other dedicated organizational units such as forums, projects, and regional offices (see figure 1). At NIA’s headquarters, about 450 employees work in one of the organizations’ sections or departments.

Historically, the different sections were autonomous associations which merged in the 1990s into a single organization. There is still a certain rivalry remaining among the sections since many member companies are (or could be) members in more than one section. The allocation of NIA’s financial resources fosters this rivalry. Member companies pay fees directly by the section they are members of. The sections transfer a certain percentage of their fees to NIA’s board to finance central activities and horizontal units.

NIA is characterized by a grown and highly decentralized organizational structure. The historically induced rivalries among the sections led to mutual unawareness of competencies and responsibilities within the organization, and thus, had a negative impact on the knowledge sharing practises. Since NIA’s services towards its member companies are mainly based on human and social capital, ERS technology was regarded to offer high potentials [21].

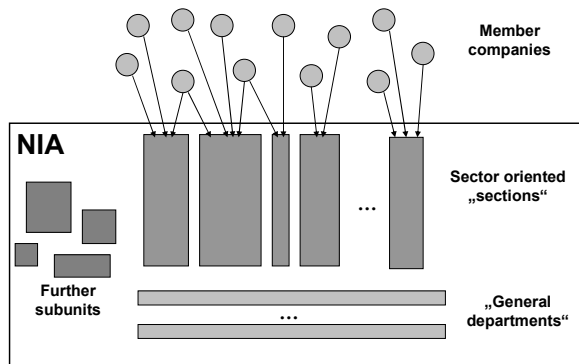


Figure 1 Organizational structure of NIA

Our work was part of a research project funded by the German Federal Ministry of Economics and Technology. The project was initiated on NIA’s initiative. The heads of two of its sections were instrumental in setting up the project: the ones on ‘agricultural machinery’ and on ‘software’. The first one was also a member of the executive board. The project was aimed at fostering NIA’s internal knowledge sharing practises and improving its knowledge-intensive services towards its member companies. Our research activities inside NIA were mainly focussed on

the agricultural machinery section to create a pilot which could serve as a reference for other parts of NIA. Hence, most of the participants were working for the agricultural sector. Additionally, employees of several other, mainly horizontal units, took part in the study. The project was headed by an employee of NIA’s subsidiary for research and development.

The research activities were framed by an action research (AR) cycle [26] and applied methods of the Integrated Organization and Technology Development (OTD) [29]. Our research activities involved three major steps:

- (1) *Requirements analysis*: In order to learn about the typical work processes, information needs and organizational culture from the workers’ perspective, we conducted 16 semi-structured interviews with employees (14) and managers (2) of NIA (cf. [21, 22]).
- (2) *System design*: Based on the results of the first step (as far as they could be understood as technical demands), we formulated basic requirements for KM support. Based on these requirements we designed and implemented a prototypical ERS, called *ExpertFinding*, in order to meet the requirements (cf. [22]).
- (3) *Roll out and evaluation*: We introduced the *ExpertFinding* system to a set of 19 (later 24) employees (referred to as pilot testers) who used the system over a period of about eight months. During the evaluation study we took 20 more semi-structured interviews with pilot testers.

To limit tensions resulting from the rivalries among the sections, requirements analysis and roll out phase focused on the agricultural machinery section and employees of different horizontal units. Most of the interviewees of the first phase participated also in the roll-out. While the results of the first two steps are described in details in [21, 22], we focus on the evaluation of the system in this paper.

We started the evaluation study in March 2006. While most of the 19 pilot testers were asked to take part, two of them joined the pilot test on their own initiative after the system launch got around. In the beginning, we offered two trainings to which the pilot testers were invited and installed the system on their computers. After 20 weeks, we extended the test site by including five employees of one of NIA’s member company. These employees also got training at the company’s headquarters.

Seven of the pilot testers were employees of the agricultural section. Additionally, different horizontal units (communications, information systems, engineering, law, ecology, and economics), the executive board, the internal publishing house and the ‘pumps and systems’-section were represented, each with one participant. Two further pilot testers belong to NIA’s subsidiary for research and development.

During the evaluation study we conducted 21 interviews in two cycles: 9 at the beginning (after the trainings) and 12 in the end of the evaluation period. 6 of the interviewees were consulted in both cycles. The interviews were recorded via tape recorder with the participants' agreement. Furthermore, over the entire evaluation study we offered technical support via telephone, e-mail, and periodic visits of the system developer (and first author). Thereby we collected user feedback of any kind – suggestions, bug reports or criticism – which was documented as well. User feedback that was gained during support activities was not recorded but documented form of field notes by the first author. Based on the feedback we updated the system periodically. New versions of the system were then rapidly installed on the machines of the corresponding pilot testers in order to get instant feedback on the newly integrated features or bug fixes – again plotting user feedback. By doing so, we applied a cyclic, evolutionary and participatory development of the *ExpertFinding* system following the framework of Integrated Organization and Technology Development (OTD) [29].

EXPERTFINDING

The subsequent paragraphs describe the design and architecture of the ERS application, called *ExpertFinding* in more detail. We motivate central aspects of the design approach by empirical findings from the requirements analysis (RE).

ExpertFinding stores and maintains expertise profiles reflecting the users' recent activities and expertise. The application's main purpose is to enable NIA's employees to find suitable experts to handle incoming requests from member companies that often are handed in a highly self-organized manner [22]. Incoming questions often need to be assigned to an appropriate expert which was identified to be a highly time-consuming task because it was not sufficiently supported by any of NIA's existing media (see below).

The *ExpertFinding* application combines two mechanisms of profile creation: The first one creates semi-automatically large scale keyword lists from arbitrary text documents (doc, ppt, pdf, html, txt.) selected from the user's file system. In order to create accurate profiles and to protect the employees' privacy, users select the documents or folders themselves. If they chose a folder, all containing documents and subfolders are selected. However, users can configurate filters to restrict the choice to certain types of document formats or subfolders. The files and folders are stored either on the user's local file system or on a shared directory system.

The resulting 'keyword profiles' typically contain up to several hundred thousands of different terms. In order to limit their size, we filtered stop words and cut less frequent terms from the keyword listings so that in the end 10.000 to 20.000 terms remained. We decided not to apply more

rigorous filter mechanisms to avoid unintended filtering of relevant keywords.

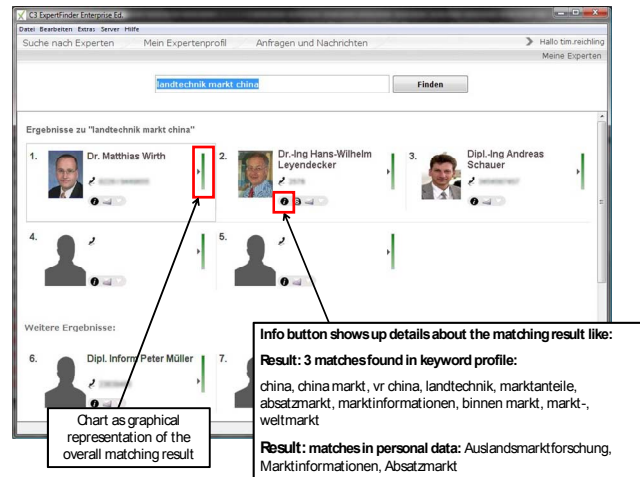


Figure 2 *ExpertFinding*: window showing a ranked list of experts (with photos if provided in the yellow-pages) and information explaining aspects of the ranking

The keyword profile was designed to satisfy two central requirements from the RE: (1) A time efficient procedure of profile creation and maintenance and (2) accurate and comprehensive expertise profiles. We assumed that the filing habits of the participants are rather stable over time. Therefore, once the files and folders are carefully chosen, adjustments to this selection are not often necessary since eventual changes with regard to documents or subfolders are covered. The described method of profile creation differs considerably from existing approaches as it explicitly involves the users in selecting appropriate resources. We propose that such user involvement is necessary in order to meet the users' privacy concerns as well as to create accurate expertise profiles.

The second mechanism for profile creation is a rather straight forward yellow-page (YP) styled form in which users can enter contact information as well as information about their educational background, job descriptions, specific qualifications, language skills etc. We included these 'YP profiles' in order to enable the users to directly shape their expertise profiles in case they are willing to [14]. Furthermore, the YP profiles should give the users a better control over the contents of their expertise profiles.

Thus, each expertise profile consists of two profile components – keyword and YP profile – which are regarded as complementing each other: The large scale keyword profiles fill up the gaps that exist within the YP profiles. The keyword profiles are created and periodically updated almost automatically without user input. In particular, additional keywords are extracted from documents which are newly stored in selected folders. These updates are expected to represent the dynamic changes in the user's focus of work and expertise. By

contrast, the YP profiles embody indicators for ‘long term expertise that do not need to be updated frequently.

The *ExpertFinding* application relies on a client-server architecture. It provides front and back end components to carry out expertise inquiries and to set up expertise profiles. It can also be used for storage and matching of expertise profiles. We decided to implement a client component rather than a web based client mainly for privacy reasons. Since the clients are installed locally on the users’ machines documents do not need to be uploaded to the server for keyword profile creation. The entire profile can be set up, inspected and eventually fixed before uploading.

We further decided to base the system on a component-based architecture which supports extension and changes of functionalities with relatively low efforts. Components are encapsulated in ‘plug-ins’ that could be updated remotely. We did that for two reasons: First we took into account the dynamic interplay between groupware applications and organizations which can lead to emerging requirements that need to be quickly integrated (cf. [14, 18]). Second, regarding NIAs organizational and IT infrastructure, the RE showed evidence that the need for a deeper integration of the ERS into the existing infrastructure would emerge.

The client system provides capabilities for expertise search. As simplicity and ease of use were required in the RE the corresponding user interface is kept very simple and straightforward, mainly inspired by the Google website (one participant of the RE described his vision of the ERS as “Google for NIA”, cf. [21, 22]). The user client shows results as a list of experts which is ordered by relevance. Furthermore, excerpts from the relevant parts of the profiles (e.g. terms that match the request) are displayed. It also provides facilities to directly contact experts mentioned in the result list via an internal messaging tool (cf. [22]).

The server provides several matching algorithms of different complexity, e.g. Latent Semantic Indexing (LSI, see [7]), to the keyword profiles. Besides LSI we created less complex algorithms that perform matching on a fairly straight forward base such as ‘summing up weights of matching terms’ (see [22]). The different matching algorithms can be set up to work concurrently or exclusive. We included multiple algorithms for matching in order to find out the most suitable during the evaluation.

EMPIRICAL FINDINGS

After having installed the *ExpertFinding* client at the pilot testers’ computers, the first steps of usage were stimulated by the developer. Typically, he would ask the users to create a profile and made them conduct some search inquiries. During his regular visits on-site to provide technical support, he would ask questions on usage patterns, and strengthen interest in the application.

While the usage patterns were differentiated, auto search was an important activity. After having created their first set of profiles most users were interested how they were

ranked with regard to search items relevant to their tasks. Surprising or dissatisfying results led to a more in depth evaluation of the key word list and modifications of the selected document folders.

Since the pilot testers from the agricultural department knew each other well and also some of the actors from the general departments, they did not search for experts too frequently. Some of them even did not bother to create elaborated profiles. However, some interviewees reported about the useful appropriation of the search function. One employee from the communications department reported that she was using this function to identify colleagues whom she could ask to write a specific article for NIA’s weekly journal.

So, the limited number of pilot testers, the fact that many of them knew each other rather well, and the stimulating activities of the developer led to rather specific pattern of usage. Auto search and profile creation were the predominate activities. When describing the results of the evaluation study in more detail, we will focus on the appropriation of the semi-automatic profile creation mechanism.

Creation of expertise profiles

We noticed typical patterns of adoption, each indicating the importance that users attach to the application. One type of user was highly involved in rendering their profile to make them reflect a maximum of expertise in as many domains as possible. For instance, we observed the head of the information systems department and the agent responsible for NIA’s website ‘developing’ their profiles against each other after the latter found out that she was outperformed on the keyword “internet” which she claimed as a central indicator of her competence. Hence, both added documents or folders to the keyword profile and edited their YP profile and checked the results of the expertise search afterwards. Obviously the order of search results was perceived highly important: Users often were upset when other (known) colleagues appeared in the result lists on a higher position on a self-occupied search term, even though they appeared among the first three hits. The converse behaviour was also observed: A pilot tester from the agricultural section (working mainly on superficial administrative stuff) entirely refused to create her expertise profile. She argued that for each possible domain there were colleagues within her department that were better candidates to ask.

The patterns of usage observed among the pilot testers strongly imply that in order to gain users’ acceptance (and assure a critical mass of users) they need to feel adequately represented by the system. This is especially given for key capabilities, e.g. people in positions of responsibility like section leaders. Even the manipulation of the result order (analogue to Google Adwords) in the interest of those capabilities was suggested during the evaluation study in case they were outperformed by ‘non-capabilities’.

The perceived significance of the system was underlined by several participants expressing that the real value of the application could not be recognized unless it was rolled out over the entire organization, including external regional departments. Along with these statements the participants expressed their expectation that this would happen quite soon, which they found desirable.

Since the pilot testers were dealing with the ERS prototype hands on, they came up with new ideas for redesign. For instance the head of the information systems department suggested generating “daily profiles”. Those profiles should offer insight to the current activities of users to avoid redundant work at different locations within NIA. As “daily profiles” require access to up-to-date data, the inclusion of e-mail messages was discussed again. Interestingly, while the use of e-mail messages was widely rejected by the participants during the RE phase, some of the pilot testers rethought their attitude towards that option. They stated that the use of certain non-private e-mail folders for profile creation could be acceptable.

An interesting problem was described at the end of the evaluation phase by a participant working in the agricultural section. When asked to explain the temporarily low level of usage in his department (even though five users from one of their member companies were added, see above), he explained that the systems’ expertise profiles could be misinterpreted by others as a sort of job description. Since there was not any detailed job descriptions given in his department, task assignment among the colleagues had developed over time and was performed in a rather informal way. While this way of task assignment worked perfectly for their department, pseudo-job descriptions like expertise profiles were regarded as a disturbing factor, causing tasks that were accomplished ‘voluntarily’ before being assigned in a ‘hard-wired’-manner now.

The head of the information systems department expressed lacking understanding when faced with the rather poor expertise profiles of the colleagues from the agricultural section. He explained that those poor profiles were likely to damage NIA’s reputation on the members’ side as they (undeservedly) created the impression that little expertise is covered by the department. Hence, he suggested that each user was responsible for suitably “blowing up” his expertise profile in order to properly represent his department. This is even more interesting in conjunction with the results above.

The extension of the system usage to member companies (realized in the evaluation study by including five users of one member company) was an upcoming issue during the evaluation study. This would enable employees of member companies to directly seek for suitable contact persons at NIA. Several pilot testers found it to be a perfectly natural step as it would decrease the work load for both internal employees and employees of member companies. In order to control the number of requests, external access should be restricted to a limited number of trusted external actors who

would need to sign in via login and password, as one of the agricultural sections employees suggested.

Keyword profiles and search results

Most of the pilot testers expressed their approval and comprehension to the semi-automatically created keyword profiles as part of the users’ expertise profiles. The choice of appropriate documents reflecting the users’ activities and expertise appeared straightforward to most of the users. The generated keyword profiles were largely judged to be accurate. These findings are widely confirmed by a brief quantitative analysis that showed promising results. The analysis was conducted by our contact person (who was familiar with the work and expertise of the pilot testers) in order to verify that the search function returned valid results. He compared the application’s matching results on a set of representative keywords with his ratings and assigned scores to the results.

However, several pilot testers (among them an employee of the economics department) stated that from their point of view the keyword profile was mainly an “extension” to the YP profiles which were regarded as the “real” expertise profiles as they could be edited directly. Since the *ExpertFinding* application weighted both profile components equally when matching profiles against requests, the employee of the economics department suggested that users should be able to define weights to indicate the importance they would attribute to each of the components. Hence, they could assign a higher weight to their YP profile than their keyword profile.

Moreover, different problems occurred during the evaluation study. Several pilot testers felt troubled by the large and comprehensive (but hardly manageable) keyword profiles that sometimes contained seemingly irrelevant or meaningless terms as a result of the non-rigorous filter mechanisms. Even though this was absolutely intended (see above) some users judged those occurrences as a system failure. For instance, ‘trivial’ keywords like the association’s name or headquarter often appeared in the keyword profiles. Although the pilot testers assumed that such meaningless keywords would not have any negative impact on the search results, they still found them disturbing.

One user of the agricultural section was stunned by the local profile creation. Even though we repeatedly pointed to the fact that there would not been any document uploaded, the user still believed that documents were uploaded to the server which prevented him from selecting documents for his keyword profile.

Another severe (even though subtle) problem occurred during the evaluation study: The problem of ‘seemingly adequate’ documents that showed up in one case where an administrative member of the standardization panel (referred to as A) conducted a straightforward choice of documents. The resulting keyword profile accurately reflected her focus of work. However, in a later interview

session with one of A's colleagues from the agricultural section (referred to as B) it turned out that the keyword profile of A and B were similar even though the nature of their competency was rather different. While A performed rather superficial, administrative jobs concerned with standardization, B was deeply involved, e.g. he worked out drafts of standardization documents. Therefore, B declared that he had a more legitimate claim to call himself an expert in that domain.

The *ExpertFinding*'s keyword profiles happen to accurately indicate the users' domain of knowledge which is supported by the above results. However, characteristics like the nature of expertise (administrative, coordinating or operative) as well as the level of expertise (strong, medium or weak competency) are not sufficiently represented. This shortcoming turned out to raise problems because both participants wanted to feel adequately represented while potential requestors seek for either content-oriented or administrative competencies.

Organizational issues

If we assume the system to be rolled out over the entire organization, certain organizational changes are likely to arise (cf. [14, 18]). The evaluation study indicates several 'organizational shifts' that may take place.

First, we discovered different cases in which employees – independent of their actual competencies – appear to be experts due their representation in already existing media. For instance, the agent responsible for NIA's website was mentioned with her full name and her e-mail address at the bottom of each web page, rendering her one of the most prominent persons all over the organization. In an interview she stated that she was indeed troubled by many requests (most of them via e-mail) that she was not responsible for. Hence, replying to these requests became a time consuming part of her job.

Other cases of 'inadequately prominent people' within the organization were mentioned by different interviewees. One relevant case is caused by the present employees' directory. It was said to be incomplete because only employees in higher positions are listed. Moreover, it contains inaccurate and arbitrary descriptions of their responsibilities and competencies provided by the included actors themselves. Finally, it is lexicographically ordered which turned out to be problematic because those actors whose names start with early letters in the alphabet were more often requested than others.

We found that persons who were more prominently represented in the company's media were troubled (or blessed – see below) more often than others. At the same time, the actual responsible or competent people were omitted due to their undeserved weak representation in these media.

Regarding the actors' expertise and their representation in the existing media, we can distinguish four categories as

shown in figure 3: (1) Actors with great expertise and adequate representation ("big experts"), (2) actors who are overrepresented and potentially troubled by amounts of requests that they are not responsible for, (3) actors who are underrepresented although they possess considerable expertise ("small experts") and (4) actors who do not possess meaningful expertise (or assume they don't) and are accordingly weak represented. The potential impact of the ERS can be regarded as a shift in the actors' representation, shown as white and grey arrows in figure 3.

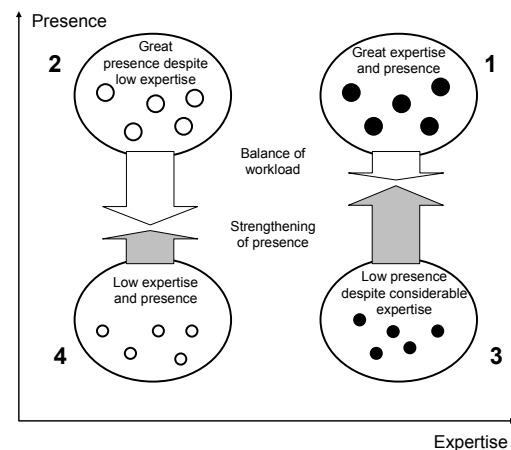


Figure 3 Impact of the ERS technology on the perceived distribution of expertise

In each category we can assume the ERS to produce 'winners' as well as 'losers'. Whether an actor understands himself to be a winner or a loser depends on how satisfied he was before and how his situation has changed due to the ERS. However, there is evidence that the impact on each of the groups is rather positive than negative. First, for the categories 2 and 3, we can assume that the impact of the ERS will be perceived rather positive since members of category 2 are taken out of 'the line of fire' and members of category 3 will be represented according to their actual expertise which can improve their reputation. Second, it is likely (although by no means guaranteed) that 'real' experts in a given domain (category 1) will show up with a larger amount of dedicated documents than non-experts (category 2). Hence, the impact on categories 1 and 2 is assumed to be asymmetric (see figure 3).

Technical aspects

Among the results of the evaluation study there are some interesting technical implications towards ERS. First, quite soon it became clear that the LSI-based matching algorithm did not return satisfactory results compared to the other matching algorithms (see above). Though we dedicated quite some efforts on fine-tuning the algorithm, the LSI results were felt to be diffuse and arbitrary by several users. This is likely to be a result of the broad nature of keyword profiles, covering large amounts of terms which do not longer provide a common meaning (as textual documents do).

Second, it became evident that the selection mechanisms for the choice of folders and files to create the keyword profile were too imprecise after changes in the organizational use of the filing system emerged. Following a mandatory guideline (that was set up while the evaluation study was ongoing), NIA's employees were only allowed to use common server drives to store their files. As a result, it became much more difficult for users to select 'their' files and folders within the directories since they were used by others as well. As most of the pilot testers complained it was far too time-consuming to single out their own files, they rather selected folders on a higher level risking a very coarse and inaccurate choice of documents, strongly overlapping with the choices of other users. So the organizational regulation with regard to the storage of files can impact the effectiveness of our approach to profiling severely.

Third, in order to clean the keyword profiles from meaningless terms (see above), one participant suggested a NIA-specific thesaurus which would contain widely used terms which would be considered to be meaningless in the context of the association. This thesaurus could also contain the family names of employees in order to satisfy the users' privacy concerns as well as legal constraints resulting from German law.

Finally, the component based architecture turned out to be useful. While the pilot testers encountered several shortcomings of and emerging requirements to the *ExpertFinding* application, we frequently needed to update the system which was considerably eased by the dynamic update mechanisms which relies on the component based architecture (see above).

Nr.	Finding	Extended requirement	Potential technical implementation
1	Basic elements of the system design were not sufficiently understood (local creation of expertise profiles, comprehensive keyword profiles)	Algorithmic transparency	Careful UI design, extended help functions, focus on these issues during roll out and training
2	Shared folders lead to improper choices of documents out of which keyword profiles are generated	Simplification and refinement of selection mechanisms	Optional selection criteria based on age, authorship, and other characteristics of files and folders
3	Family names and organization-specific terminology show up in the keyword profiles, which upsets the users and may violate privacy concerns	Extended privacy options Algorithmic transparency	Implementing a thesaurus specific for each organization which contains names and certain terminology
4	Need to individually specify weights for certain profile components	More focus on user control	Support configuration of the weighting algorithm
5	Lacking visibility of simultaneous accomplishment of similar tasks	Highly up-to-date profiles	Restricted and user controlled access to highly up-to-date data sources (like e-mail)
6	Nature and level of expertise are important properties for potential requestors, which are not sufficiently covered by the <i>ExpertFinding</i> system	Refined model of expertise	Include additional types of data based on users' self-perception or mutual ratings
7	Allowing externals, such as employees of member companies, access to the system may enable head hunting activities	Ensure that externals access can be controlled with regard to the types of data being disclosed	Guidelines for visibility settings Implementation of filters to avoid disclosure of sensible information to externals
8	Over- or understatement when creating expertise profiles are typical patterns of adoption	Ensure reasonable ways of usage within the organization	
9	Expertise profiles can be interpreted as (mandatory) job descriptions	Ensure congruency between expertise profiles and actual job descriptions	
10	ERS may produce 'winners' and 'losers'	Make 'winners' become the larger group	

Table 1 Extended requirements for ERS technology

Extended requirements

As a result of the roll-out, we can summarize requirements of ERS technology (see table 1). We also elaborate on potentials for reimplementation. While the first seven findings in table 1 are rather clear, the findings 8 – 10 need some elaboration. First, they do not imply any technical changes. Second, it is unclear whether they require planned interventions or will emerge over time. So at this point, we need additional long term investigations.

Regarding finding 8, it seems likely that those actors who overstate their own expertise (see above) may over time decide for more realistic expertise profiles after they are troubled with requests they cannot answer. The perception that expertise profiles may get the character of a job description (finding 9) is another issue that needs further investigation. Stable task assignments and existing job descriptions may turn out to be a necessary precondition when applying ERS technology. Finding 10 does not imply the need for planned intervention unless significant numbers of ‘losers’ appear. This again is an issue of further long term investigations.

CONCLUSIONS

The empirical results of the study provide new insights into practises of ERS appropriation. We were able to evaluate the design approach of semi-automatic profile generations over a period of eight months, much longer than almost all evaluation studies in this domain.

As far as the study deals with profiling behaviour, the small number of the participants does not weaken the results significantly. The users generated different versions of their profiles and evaluated them mainly by means of auto search. The findings concerning users’ effort to set up their expertise profiles, the modes of self-presentation, users’ privacy concerns are grounded in real world experiences. A larger number of participants would probably have strengthened the effects observed (and led to additional ones).

Due to the small number of participants and their partial familiarity with each other, the users searched only occasionally for experts and evaluated matching results for this purpose. While hands-on experience allowed users to better anticipate organizational impacts of ERS functionality and additional experiences with NIA’s website were existing (see ‘organizational issues’), these results have to be interpreted with more care.

With regard to semi-automatically created profiles, the study indicates that it can lead to appropriate expert profiles for most users engaged. Most of the hits the *ExpertFinding* application returned on inquiries were owed to the keyword profiles (instead of YP profiles). In most cases the occurrence of actors on the result lists was perceived reasonable even though the order of results was criticised in some cases.

Our study led to some new insights with respect to the design of ERS. First, the importance of auto-search

activities became rather obvious within NIA. Users may appreciate a function which indicates the linkage between a selected set of documents and its effects on their ranking with regard to specific keywords. Second, we underestimated the need for more fine-grained mechanisms to select textual documents. It turned out that authorship and creation date are important filters for document selection, which should be supported in later versions of the system. Additionally, an analysis of e-mail communication could hint to individual expertise specifications in particular knowledge domains [8, 16]. However, e-mail profiling was still declined by most users due to privacy reasons. Still, the hand-on experience with ERS functionality had slightly changed their attitude compared to the prestudy [22].

Our findings are consistent with former studies that found ERS can generate accurate but not always complete expertise profiles [17]. As [14] suggests, the users’ understanding of the matching algorithms deeply influences the acceptance of such systems. In case of ERS we believe that the user understanding of how the system works (underlying algorithms) is as important as the usability of the system because both influence the users’ perception of the control they can exercise.

The reported findings significantly add to the state of the art with regard to the diffusion of keyword profiles (according to domain, degree and nature) and to the observed shift in the perception of expertise. The present study showed more clearly than other studies before [10, 14, 17] that the organizational recognition to be seen as a ‘competent contact person’ plays an important role. First, this recognition influences the perception of ‘responsibility’ for expertise related inquiries, and therefore, potentially compensates for the additional workload caused by these requests. Second, this recognition might be a career advantage due to the perception of competencies and performance. However, certain actors might fear the potential loss of reputation due to ERS generated profiles, and therefore, reject these applications.

We observed actors developing their expertise profiles while others kept their profiles rather small. The ERS appears to be perceived as a meaningful medium for self-presentation. It can impact the organizational perception of individuals’ expertise. The acceptance of ERS may suffer if ‘winners’ worry about additional workload from requests or ‘losers’ are scared by a potential damage of their reputation. While our study pointed to the importance of these issues, a more profound analysis will be necessary comparing different ERS implementations and organizational settings.

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