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Recommending Knowledgeable People in a Work-Integrated Learning System

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Abstract

According to studies into learning at work, interpersonal help seeking is the most important strategy of how people acquire knowledge at their workplaces. Finding knowledgeable persons, however, can often be difficult for several reasons. Expert finding systems can support the process of identifying knowledgeable colleagues thus facilitating communication and collaboration within an organization. In order to provide the expert finding functionality, an underlying user model is needed that represents the characteristics of each individual user. In our article we discuss requirements for user models for the work-integrated learning (WIL) situation. Then, we present the APOSDLE People Recommender Service which is based on an underlying domain model, and on the APOSDLE User Model. We describe the APOSDLE People Recommender Service on the basis of the Intuitive Domain Model of expert finding systems, and explain how this service can support interpersonal help seeking at workplaces.

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1. Introduction

Since more than a decade, there is growing interest in making workplaces more effective learning environments (e.g., [1]). It is generally acknowledged that computers and other technologically driven media offer significant opportunities for new forms of learning at work. Increased efforts have been made on utilising new software technology to deliver learning support. Lindstaedt et al. [2] have coined the term *work-integrated learning* (WIL) in order to refer to a learning paradigm focusing on seamlessly integrating working and learning. In line with Billett [3], we understand learning at work as the *acquisition of knowledge and skills as a function of participation in authentic tasks, with support and guidance, either direct or indirect, from others more skilled*. What follows from this definition is that (work-integrated) learning is social in nature. It is widely acknowledged that knowledgeable colleagues are one of the most important sources of knowledge for workers. For instance, Kookan et al. [4] in their

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workplace learning study observed four “solution categories” of persons seeking help at their workplaces: *interpersonal help seeking*, *seeking help from paper based written material*, *seeking help from digital written material* and *practical application* (“trial and error”). According to the authors, of these strategies, interpersonal help seeking is the one that is applied most frequently (in 70% of the cases).

Finding knowledgeable persons, however, can often be difficult for several reasons. First, the number of workers within an organization may be too large to know the fields of expertise of everyone. Second, even if workers work together in one and the same office, they are often not aware of what their colleagues are working on. Third, competency databases, if available, are often outdated because manually maintaining these databases is costly. In addition, such competency databases often comprise rather coarse-grained competencies (e.g. „programming skills“). This may result in the situation that most of the questions that occur are posed to a relatively small group of „experts“, even though other persons also might have been able to help.

Adaptive systems (e.g., [5]) and recommender systems (e.g., [6]) can support the process of identifying knowledgeable colleagues. In our view, within an organization all employees are potential sources of knowledge who can help in a very specific context. Imagine, for example, Paul who is new in a company offering consulting for innovation management. Paul has a degree in business economics, and basic knowledge of creativity techniques. His supervisor asks him to prepare a creativity workshop for a project with customers from the automotive industry. Because Paul has never prepared such a workshop in practice, he may benefit greatly from communication with a colleague who has more profound knowledge about creativity workshops than he has. One such colleague is Susan. Susan has a background in design, and a lot of knowledge about creativity techniques but only basic knowledge about economy. Even though Susan is not an “expert” in any absolute sense, she may be able to help Paul in preparing his creativity workshop because she complements his competencies. This scenario illustrates: To recommend knowledgeable people who can help in a specific situation, the system should take into account the current goal of a worker (e.g., a task and the according demands the tasks puts on the worker’s skills) as well as the skills that a worker already has available.

Context detection agents (e.g., [7]) have been proposed to automatically detect tasks or goals of users. Such agents are observing user interactions (e.g. keystrokes, mouse movements, applications specific actions) and compare them to previously learned interaction patterns. In order to identify the skills a user already has available, a user model (e.g., [8]) is needed which is continuously updated according to each user’s knowledge state. Based on the information in the user model, an expert finding system can suggest knowledgeable persons.

The work underlying this paper has been carried out in the course of the integrated EU-project APOSDLE (Advanced Process-Oriented Self-Directed Learning Environment, www.aposdle.org). In this paper we present the APOSDLE People Recommender Service, a service which is based on the APOSDLE User Model [9], and which takes into account the user context for identifying knowledgeable persons within an organization. In the following, we will discuss different approaches to recommending knowledgeable people (Section 2), analyse the requirements for user models to support people recommendation in WIL (Section 3), and present the APOSDLE People Recommender Service (Section 4).

2. Recommending Knowledgeable People

Much work has been done, both in industry and academia, on developing new approaches to recommender systems over the past decades (for a comprehensive review see e.g., [6]). However, because recommender systems constitute a problem-rich research area, and because of the abundance of practical applications that help users to deal with information overload and provide personalized recommendations, the research interest remains still high. A taxonomy compiled by Montaner et al. [10], categorises recommender systems according to two important aspects of recommender systems, namely *profile generation and maintenance*, and *profile exploitation*. Profile generation is comprised of the representation and the creation of a user profile based on e.g., a user’s interests, purchases items, or demographic information. Examples of user profile representations are history based models, vector space models, or different types of networks. The process of creating a user profile is described by Montaner et al. [10] as *profile learning technique*. Profile learning techniques range from using the raw data from available sources to clustering or classification of data. To address the fact of changing user behaviour, recommender systems maintain their profiles over time. Maintenance techniques can, for example, be implicit or explicit relevance feedback, or the implementation of forgetting functions. With profile exploitation, Montaner et al. [10] describe the

usage of information available in user profiles to recommend users e.g., new products or people interested in similar topics. Well known recommendation techniques are collaborative, content-based or demographic filtering.

In work-integrated learning, recommending knowledgeable persons means finding people within the organization who have expertise related to the current (learning) goal of a user. Similar functionality has been realized by expert finding systems. For instance, the MII Expert Finder [11] analyses documents authored by a company's employees to build up a name-topic mapping for recommending experts. Extracting information from outgoing emails, stored chats and profiles, and user details from directories are utilized in the SmallBlue system [12] to provide a ranked list of persons based on a search query. Both the MII Expert Finder and SmallBlue are designed as centralized systems which collect all information in a central repository to apply algorithms for recommendation. A decentralized approach was presented by Vivacqua and Lieberman [13] who developed expert-finding agents running on a developer's computer and investigated Java code written by this developer. To find an expert, an agent asks other agents on a network about the expertise they can provide, and applies a similarity model to compile a list of knowledgeable users. Maybury [14] reports on the challenges of expert finding systems, and gives an overview of how these challenges were addressed in existing commercial products. Additionally, most of the tools provide ways to manually specify personal expertise profiles or keywords.

Yimam-Seid and Kobsa [15] provide an in-depth analysis of the expert finding problem, and give an overview over existing non-commercial systems in this domain. The authors present what they call an Intuitive Domain Model of Expert Finding Systems. The model is a faceted classification scheme to describe expert finders. In line with the Intuitive Domain Model, the following considerations have to be made when designing an expert finder for WIL:

1. What are the criteria based on which user expertise is inferred by the system?
2. What are the user interactions with the system (i.e. operations) from which the expertise of the users can be derived?
3. How is the expertise derived from the user interaction with the system?
4. What is the underlying model of expertise?
5. How can users seek for experts within the system?
6. How does the system respond to a request for an expert?
7. How is the result presented to the users?

With regard to (1), in WIL, expertise can manifest itself in various ways, such as the authorship of documents or publications, or the acquisition of projects. These criteria of who is an expert may also vary in different organizations. Typically, workers at their workplaces are subjected to time pressure. Thus, in order to derive information of who is an expert, the challenge in WIL related to (2) and (3) is that the system can identify expertness as unobtrusively as possible in order to not disturb the users instead of helping them. To define who is an expert in a domain, an underlying model of expertise is needed. Often, organizations have models about concepts of the learning domain and their relationships. Such centralized organizational models can then serve as the basis for identifying the level of expertise of individual employees in each of the concepts in the enterprise model (4). Two different scenarios are conceivable in WIL how users could want to seek for experts within the system (5): First, a user might want to learn about a specific topic. Then, he or she could access the expert finding system and search for a knowledgeable colleague who can provide help in this topic. The second scenario is that a user does not know what he or she is looking for. Instead of active search, the expert finder could recommend a knowledgeable person who addresses the knowledge need of a user by taking into account the users' context. In such a system, no active search of the user is necessary, the system knows what information a user needs in a learning situation. It is especially this second scenario that we want to address with our contribution. How the system responds to a request for an expert (6) and how the result is presented to the users (7) are design decisions that are not specific to WIL systems.

Obviously, for recommending knowledgeable people, a user model is needed which represents the knowledge and skills of each individual user, and which is continuously updated. In the following, we will discuss existing approaches to user models and user modelling, and the specific challenges for WIL.

3. Requirements for WIL User Models

In order to recommend experts to users in an adaptive manner, an expert finding system needs to have a model of

the users' expertise. This model shall be termed user model (e.g., [8]). The user model is described as "a representation of information about an individual user that is essential for an adaptive system to provide the adaptation effect, i.e., to behave differently for different users" ([8], p. 3). The user model constitutes the rationale for individualized learning opportunities of each worker, and also for the decision of who is an expert in a concrete learning situation. Typically, for every individual user, an instance of the user model is created which holds the user's parameter-value for each of the topics in a domain. The user model must be updated continuously throughout the interaction of the user with the system.

Ideally, each user's knowledge and skills should be determined based on his or her normal work activities. Various approaches have been suggested for automatically maintaining user competency profiles in organizational databases, e.g. based on document authorship or name-concept co-occurrences (for overviews see [14] and [15]). A theory-based approach has been proposed, for instance, by Ley and Albert [16] who suggest inferring employee competencies from past task performance.

What all these approaches have in common is that deriving information about user expertise from user interaction with the system (e.g., from document authorship, communications, e-mails) may lead to an inaccurate expertise model. That is, inaccurate information may be represented in the users' profiles and as a consequence, recommendations maybe wrong. Thus it is important that users have the possibility to access and edit their profiles. Such functionality has been presented in the context of research into open learner models (e.g., [17]). A further advantage of open learner models is that they enable reflection, the planning of individual learning, or monitoring one's own learning progress.

A further challenge in building user models for WIL is that typically users learn from diverse sources (document repositories, portals, emails), and that there is no central learning system. Therefore, user activities have to be collected from interactions with these different sources. A way to address this challenge has been suggested e.g., with the CUMULATE server by Brusilovsky [18].

Summing up these considerations, user models for supporting work-integrated learning should (i) be as unintrusive as possible, that is, the efforts for users for maintaining their profiles should be minimized, (ii) they should be able to collect data from various sources and integrate them, and (iii) they should be accessible to its users in order to improve accuracy, and to support reflection and learning.

In the following, we describe how these requirements on user models for people recommenders in WIL were taken into account in the APOSDLE system. We will then present the APOSDLE's expert finding system called People Recommender Service, and its characteristics based on the Intuitive Domain Model developed by Yimam-Seid and Kobsa [15].

4. APOSDLE – Recommending Knowledgeable People

The aim of the adaptive learning system APOSDLE is to improve knowledge worker productivity by supporting knowledge workers at their workplaces within everyday work tasks. A comprehensive overview of APOSDLE and its functionality has been given in Lindstaedt et al. [19]. Here, we only describe the mechanisms that are related to the expert finding functionality.

APOSDLE is based on a domain model. The domain model is an ontology that represents tasks in the learning domain, topics in that domain, skills that are required for performing the tasks, and a "requires-relation" between tasks and skills. The "requires relation" for a pair (task, skill) means that performing the task requires the skill. The fact that the skills are explicitly modelled in the domain model is exploited for building and maintaining the APOSDLE User Model, as we will see in Section 4.1.

Within APOSDLE, recommendations of colleagues are always provided depending on a user's current topic or work task. Starting from a task or topic and taking into account a user's knowledge and skills, resource and people lists are presented to the user. Since we do not have a learning system as the central application but learning is integrated into the work environment, we need a way of observing what users are doing in order to identify their current task or topic they are working on. In APOSDLE, the task and topic detection is realized by a specialized agent (Lokaiczky et al. [20]) part of the APOSDLE Client. This agent observes the user interactions (e.g., key strokes, mouse movements, applications specific actions) with typical MS Office and internet applications and compares them to previously learned interaction patterns of the organization. APOSDLE monitors a user's daily work activities. Whenever APOSDLE detects that a user is performing a task, the system makes inferences on the

skills that a user needs to have in order to perform the task successfully. The requirements of the task are compared to the user's knowledge and skills as represented in the user model, and a set of skills that the user needs to acquire in order to perform the task successfully is derived. This set of skills constitutes a user's learning need. For each of these skills in the user's learning need, APOSDLE recommends learning materials and knowledgeable colleagues. Similarly, if APOSDLE detects that a user deals with a certain topic, the system suggests learning materials and knowledgeable colleagues directly for this topic.

For instance, remember Paul, our innovation consultant from the introduction. Imagine that Paul interacts with various desktop and web applications on this computer. From this interaction, APOSDLE recognizes that Paul is trying to prepare apply a creativity technique in a workshop (task “Kreativitätstechniken in Workshop anwenden”, left pane of Figure 1). APOSDLE compares the requirements of this task as modelled in the underlying domain model with the skills Paul has available as represented in the user model. APOSDLE detects a learning need comprising of the “ability to apply creativity techniques”, and the “knowledge about how to prepare an agenda for a creativity workshop”. In order to support Paul, APOSDLE suggests a variety of learning materials (right pane of Figure 1), including a list of knowledgeable colleagues who can provide help. On the top of the list of

The screenshot shows the APOSDLE Suggests application interface. At the top, there is a navigation bar with buttons: 'Suggests', 'Search', 'My APOSDLE', 'Add Resource', 'Preferences', and 'Help'. Below this, the main header reads 'ISN > Kreativitätstechniken in Workshop anwenden'. On the left side, there is a sidebar with a search bar containing 'kreativt' and tabs for 'Topics', 'Tasks', 'Detected (7)', and 'History'. The 'Detected (7)' tab is active, showing a list of tasks including 'Projektakquise', 'Projektentwicklung', 'Ideen finden', 'Kreativitätstechniken in Workshop anwenden' (which is highlighted), 'Workshop nachbereiten', 'Ideenbewertung', 'Ideenrealisierung und Coaching', 'Projektabschluss', and 'Wissensaufbereitung'. At the bottom of the sidebar are buttons for 'View as a process' and 'Explore links between topics and tasks'. The main content area on the right has a section titled 'A short description of Kreativitätstechniken in Workshop anwenden' with the text 'Agenda erstellen, Präsentation (Projekt) erstellen, Methoden und Tools auswählen.' Below this is a filter section 'Filter Suggestions based on your Experiences:' with a dropdown menu set to 'Only show resources relevant to'. The results section shows '53 Results: Found 2 People, 51 Snippets' with a 'Next page' link. The first two results are people: 'Schneider(1) Pierre' and 'Fischer(3) Paul', each with 'Contact', 'Show Business Card', and 'Share' icons. The next three results are documents: 'Unbekannt about Kreativitätstechniken' (Found in Kap2_00.doc), 'Mehr zu über Kreativitätstechniken' (Found in neurovation_4.09.wmv), and 'Mehr zu über Agenda' (Found in http://www.test.at), each with 'Open', 'Collect', and 'Share' icons.

Figure 1: APOSDLE Suggests application recommending people and other resources (e.g., documents, videos, links)

knowledgeable colleagues is Pierre Schneider (“Schneider (1) Pierre”), who has both these skills and thus can help Paul in his task. Paul decides to contact Pierre via the APOSDLE collaboration wizard [21], a collaboration tool embedded in APOSDLE. In the following, we will describe in more detail the APOSDLE User Model and the mechanisms of the APOSDLE People Recommender Service.

4.1. The APOSDLE User Model

As mentioned above, for user modelling within APOSDLE, we exploit the information in the underlying domain model. The APOSDLE User Model is a layered overlay (e.g., [8] p. 5ff) of the skills in the domain model: For each of the skills, different types of information are stored separately, i.e. in different “layers” of the user model. From a technical perspective, this has the advantage that algorithms for diagnosing user skills from different types of information about users can be easily changed.

Many domain model based adaptive learning systems build user models in an intrusive manner: they require explicit feedback from the user and often at a significant level of user involvement (Jameson [5]). While in traditional learning systems user models are typically updated by means of tests, testing is not a viable option in work integrated learning (WIL) systems. Thus, in APOSDLE, knowledge and skills of the users should be inferred from different types of user interactions with the system.

The idea of inferring a user’s knowledge from different types of user actions is not new. Well-known adaptive learning systems such as ELM-Art [22] take into account different types of so-called evidence-bearing events, that is, different kinds of user actions that indicate user knowledge. Evidence-bearing events within ELM-Art can be “providing an answer to a test item”, or “visiting a page”.

The APOSDLE User Model is automatically maintained applying the approach of knowledge indicating events (KIE). In a nutshell, different types of naturally occurring actions of users are observed and inferences are made on the user’s underlying knowledge level in a certain topic. To give an example, the repeated execution of a task “preparing a creativity workshop” can be seen as a KIE for topics such as “creativity technique” and “workshop moderation”. Another KIE for the topic “creativity technique” is that a person has been contacted repeatedly about this topic.

An analytic approach was taken in APOSDLE to identify KIE. First, we detected all possible actions that users can undertake when interacting with APOSDLE. Then, for each of these actions, we decided whether they indicate learner, worker or supporter level (or none of these) of a person in a specific topic. Examples of KIE that indicate learner level include “creating a learning path for a topic”, or “viewing a learning hint for a topic”. Examples for KIEs that imply worker level in a topic are “performing a task that is related to the topic” or “viewing a document about the topic”. KIE that indicate supporter level for a topic are “being contacted by another person about the topic” and “editing an annotation for the topic”.

Whenever a user executes a knowledge indicating event related to a specific topic, (e.g. creativity technique) within the APOSDLE environment the counter of that topic is incremented in his or her user model. Consequently, the APOSDLE user model contains a value for each user and each topic at any time during system usage. In APOSDLE, three different levels of expertise are distinguished: Learner, Worker and Supporter. For instance, “carrying out a task” is a KIE for the “Worker” level, whereas “being contacted by another person” would indicate a “Supporter” level. Thus, whenever a KIE occurs within the APOSDLE environment, the levels for all topics related to the KIE are updated. This means, at any point in time, an algorithm in the APOSDLE User Model decides in which level of expertise a user is with respect to every topic in a domain.

The APOSDLE User Model is implemented as a Java component integrated into the APOSDLE Platform. Each feature (e.g., user model, retrieval of documents, storing of annotations, etc.) is provided as individual web service, and is accessed by APOSDLE Clients running on user’s desktop or laptop computers. The APOSDLE User Model is structured into three types of services: Logging services, Inference Services and Production Services. Logging services are responsible for updating the APOSDLE User Model with newly observed KIE, and thus provide the basis for all other services. Different application sensors (e.g., Microsoft Office, Firefox Browser, Windows Explorer, etc.) installed together with the APOSDLE Client send detected user activities (such as task executions, collaboration events) to logging services of the APOSDLE Platform. Pre-processing of incoming user activities is handled there. This involves the transformation of user activities into a format required by the user model, and enriching incoming data with timestamps and other system related information. Inference services process and interpret KIE to draw conclusions about different aspects of users, such as levels of knowledge. Production Services make the stored KIE available to applications within the WIL environment. Based on the specific requirements of the client, production services filter or aggregate KIE – they provide specialized views on the KIE. Each user can access the information stored about him or her in the APOSDLE User Model in a visual system component (open learner model) called MyExperiences. MyExperiences is APOSDLE’s solution to visualise the User Model and

gather feedback on inferred knowledge levels. On top of the APOSDLE User Model runs APOSDLE's People Recommender Service which is presented in the following section.

4.2. The APOSDLE People Recommender Service

The APOSDLE People Recommender Service aims at finding people within the organization who have expertise related to the current learning goal of the user determined by a task or topic he or she is working on. Users specialised in certain topics have high knowledge levels for these topics in their user models. To infer knowledgeable users, the APOSDLE People Recommender Service uses the APOSDLE User Model to access user-related information. To process user-related information, the APOSDLE People Recommender System can be configured with different algorithmic components executing the recommendation task. One of the algorithms retrieves the history of all KIEs related to a topic from one of the APOSDLE Production Services and generates a user-knowledge level matrix. The user-knowledge level matrix is calculated by summing up all KIEs mapped to a knowledge level. A row of the matrix specifies whether a user is currently categorized either as learner, worker, or supporter. In the next step, the algorithm removes all users with lower knowledge levels compared to the user receiving the recommendation. The remaining users are then ranked according to their knowledge levels. The most knowledgeable user will be ranked highest. Moving back to the scenario from the introduction the People Recommender Service recommends Susan to Paul as a knowledgeable person because Susan has a higher knowledge level. Knowledgeable persons are found by comparing the current knowledge levels of all users with the knowledge level of the user who will receive the recommendation. Another algorithm applies a weighting function boosting, lessen, or even masking out certain KIEs when creating the user-knowledge level matrix. Additionally, we have implemented a basic version of a forgetting function which applies a window on the history of KIEs. With this window it is possible to take into account a certain timeframe only.

To compare APOSDLE's People Recommender Service with other expert finding systems, in the following we classify it according to the Intuitive Domain Model for Expert Finding systems [15] and summarise it in Table 1. In order to deduce the expertness, an APOSDLE Logging Service tracks specific user activities associated with topics in the underlying enterprise models and stores these activities together with the respective topics in the user model (expertness deduction operation). These user interactions are interpreted as KIE for three levels of expertise: learner, worker, and supporter. KIE can be interactions with the APOSDLE Desktop Client, or interactions with other programs such as web browsers, office applications etc. (Expertise Indicator Source). The expertise indicator extraction operation is domain knowledge independent; a topic-name-association is derived from user behaviour. APOSDLE can be customized to any organizational learning domain without changing the expertise indicator operation of the People Recommender Service. The underlying expertise model is a centralized enterprise model that comprises tasks, topics and learning goals of the application domain. The APOSDLE User Model is an overlay of the topics in the APOSDLE enterprise model. In order to find a knowledgeable colleague, a user can either search directly for a task or topic within APOSDLE, or the task or topic is automatically identified by a context detection agent (query mechanism). In order to recommend knowledgeable persons, the APOSDLE People Recommender Service uses exact match of expertise vectors for a range of topics related to a task, or for a single topic (matching operations). Inferences on relations between tasks and topics are made based on the learning goal model.

Table 1. Classification of APOSDLE People Recommender Service according to the Intuitive Domain Model of Expert Finding systems [15].

Domain Factors	APOSDLE People Recommender Service
Expertness Deduction Operation	User activities associated with topics in the enterprise model; explicit feedback from user about deduced expertise
Expertise Indicator Source	User interactions with the APOSDLE Desktop Client (e.g., viewing and annotating documents, contacting people) and other programs (e.g. searching for a topic in a web browser, creating a document with an office application)
Expertise Indicator Extraction Operation	Domain knowledge independent; Topic-name-association derived from user interactions
Expertise Model	Associated to user model which is an overlay of the centralised enterprise model
Query Mechanism	Explicit query for a task/topic of interest; Induction of user's needs with context monitoring agent
Matching Operations	Exact match of expertise vectors for a single topic, or for a range of topics
Output Presentation	Ranked list of knowledgeable users, personal information, tag cloud of topics most worked on

The retrieved collection of knowledgeable colleagues is presented to the user in a ranked list (output presentation). Clicking on the name of a knowledgeable colleague, the user can inspect organizational (department, contact details, etc.) and personal information (name, picture, etc.) about the colleague.

When a user clicks on the “contact” icon below the name of a person in APOSDLE Suggests, APOSDLE displays a ranked list of communication tools (e.g., Skype, email, phone, etc.) to choose from. The ranking of communication tools in the list is based on a media selection model for intra-organizational collaboration [21] which takes into account communication preferences of both parties (knowledge seeker and one or more knowledgeable people) involved.

4.3. First Steps in the Layered Evaluation of the APOSDLE People Recommender Service

Evaluating the APOSDLE People Recommendation Service means to investigate if the persons suggested by APOSDLE are really able to support a worker in a task at hand for which he or she needs help. As described above, people recommendations are the result of complex inferences within the APOSDLE system: Based on a domain model, and on a mapping of KIE to the three different levels of user knowledge, each user's knowledge is diagnosed. This diagnosis then builds the basis for identifying the learning need of a person, and this learning need, again, determines which other person may be able to provide help.

Obviously, evaluating the People Recommender Service is not straightforward but constitutes a complex research question which has to be broken down further into smaller sub-questions. In the context of adaptive learning systems, this procedure of breaking down the complex evaluation process into smaller sub-steps has been termed *layered evaluation* (e.g., [23]). Concretely, at least the following sub-research questions have to be answered when evaluating the APOSDLE People Recommender Service:

1. Is the mapping of KIE to knowledge levels valid?
2. Is the algorithm for inferring a user's knowledge level from KIE valid?
3. Is the learning need of a person correctly detected for a task at hand? This refers to the validity of the underlying domain model: are skills correctly assigned to tasks, so that missing skills for performing a task can be inferred?
4. Are the algorithms for recommending knowledgeable people valid, i.e. can suggested persons really help in the situations at hand?

At the time of the workshop, we have addressed questions (2) and (3) in our research work. In order to answer the question if the algorithm for inferring a user's knowledge level from KIE is valid, we have carried out a simulation study where six different algorithms were compared in APOSDLE Deliverable D2.12 ([24], p. 55ff). The algorithm

which performed best in terms of correctness of the decision, and sensitivity to changes in user knowledge levels was then implemented in the APOSDLE prototype for a three month workplace evaluation in four real application domains. A comparison of the user knowledge levels as inferred by APOSDLE based on KIE with self- and peer assessment is currently under way. First findings are described in APOSDLE Deliverable D2.12 ([24], p. 98ff).

The issue of whether the detected learning need is correctly detected by APOSDLE (3) has been part of the study by Ley et al. [25]. Moreover, the question if the underlying domain models are valid has been extensively discussed in Kump [26].

The next step in the evaluation process will be answering the question if the mapping of KIE to knowledge levels is valid (1), and if there are differences between organizations. Therefore, an in-depth analysis of persons with different knowledge levels will be needed. Eventually, having fulfilled all these pre-conditions for suggesting knowledgeable persons within APOSDLE, the final step in the layered evaluation of the APOSDLE People Recommender Service will look at the question whether the algorithms for recommending knowledgeable people are valid, and if the suggested persons in a given situation are really able to provide help (4).

5. Conclusion and Outlook

Interpersonal help seeking is the most important strategy of how people acquire knowledge at their workplaces. Finding knowledgeable colleagues, however, can be difficult for several reasons. Expert finding systems support the process of identifying knowledgeable colleagues thus facilitating communication and collaboration within an organization.

Two challenges in finding knowledgeable colleagues have been addressed with this paper, namely the non-invasive diagnosis of user knowledge levels in different topics, and the recommendation of knowledgeable persons for WIL. We have discussed necessary characteristics of people recommenders and expert finding systems for WIL, and identified challenges for the underlying user model. Then, we presented the APOSDLE approach to user modeling based on KIE, and the APOSDLE People Recommender Service.

Besides technical measures to enhance user privacy, the following implications were derived by to allay fears of users with regard to privacy: System developers must clearly communicate the benefits of their services; if users perceive value in the personalization, they are considerably more likely to use these systems and to supply the required personal information. Moreover, users should be given ample control over the storage and usage of their data.

Our work suggests several avenues for follow-up. As mentioned above, one next step will be to evaluate the algorithm for recommending knowledgeable people given a valid user model. Moreover, research must focus on the suitability of different KIE for diagnosing knowledge levels, which may also depend on the organizational setting. During the evaluation phase of the APOSDLE Project at three different partners, we gathered a lot of user model data which will help us to assess the current implementation of the People Recommender Service, and will be used to improve future versions. Moreover, we are currently working on including a variety of additional KIE such as collaboration events and document creation. We also plan to incorporate negative KIE, such as unsuccessful task executions. Another way to further develop the People Recommender Service in APOSDLE will be to exploit organisational structures in order to provide multidimensional rankings of knowledgeable colleagues. For instance, lists of knowledgeable persons could be filtered by organisational department, or projects in which they are working.

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