Determining Information Relevance based on Personalization Techniques to Meet Specific User Needs

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Abstract The support of workplace learning is becoming increasingly important as change in every form determines today's working world in the industry and public administrations alike. Adapting quickly to any kind of change is just one aspect. Another is dealing with the information relevant to this change. A recommender system for workplace learning was developed within the European funded project Learn PAd. Even if the information is filtered based on a learner's context with the help of the recommender, information overload remains a problem. It is not only the sheer amount of information but also the (often little) time for processing it that adds to the problem, time needed to assess the quality of the information according to its level of novelty, ambiguity, etc. Therefore, we enhanced the Learn PAd's recommender by implementing a personalization strategy to filter (recommended) information based on a learner's context. Our research work follows a design science research strategy and is evaluated in an iterative manner, first by comparing it to previously elicited user requirements and then through practical application in a test process conducted by the project application partner.

Keywords Workplace learning, information overload, personalization, recommender system

1 Introduction

Workplace environments are becoming increasingly complex: many knowledge workers have to digest increasingly larger amounts of information and have to deal with change—for example in the context of public administrations the changes of regulations—that occur at a fast rate. This situation requires constant learning and efficient ways of searching for and selecting relevant information.

Within the Learn PAd[1] EU research project, novel learning approaches and solutions for workplace learning have been introduced (De Angelis et al. 2015). Therefore, a recommender system was developed that considers a learner's context regarding tasks she or he has to perform in business processes, organizational knowledge about his or her position in the organization and, his or her current skill level and working experience (Emmenegger et al. 2016). Based on this, the Learn PAd recommender suggests learning help from experts who might be contacted for

[1] see: http://www.learnpad.eu

advice, from similar cases that might be taken into account or from task descriptions and learning experiences that are available in the Learn PAd Wiki and in conventional learning material like books, audio and video files. Thus, learners are proactively provided with the help that they (are likely to) require, without having to search for it.

However, over time recommending learning help based on context information is not sufficient because the amount of relevant information is increasing constantly. Thus, information overload becomes a problem in workplace learning even if the information has already been filtered, based on a learner's context. Moreover, it is not only the sheer amount of information but also the (often little) time for processing it that adds to the problem; time needed to assess the quality of information like the level of novelty, ambiguity, uncertainty, intensity, or complexity (Lincoln 2011). For instance, in the Learn PAd system, learners are encouraged to contribute reports on their own relevant experiences—because these reports may grow large over time, filtering the relevant sections would contribute to keeping the information load at bay.

Therefore, Learn PAd's context-based recommender has been enhanced by personalization in order to (further) restrict the amount of suggested learning help.

The applied research method is design science research (Hevner & Chatterjee 2010). Since context information (e.g. about business processes, user tasks he or she has to perform in business processes, organizational knowledge about his or her position in the organization and his or her working experience) is represented in an ontology the method is complemented by the approach of Grüninger and Fox (1995) for ontology design and evaluation.

The chapter is structured as follows: In Section 2, we introduce the main concepts of the Learn PAd project to provide the background of the study. In Section 3, we give an overview of related work. Then we detail our approach (Section 4). In Section 5, we provide details on the performed evaluation (Section 6) and conclude in Section 7.

2 Background of the Study

In this chapter we briefly introduce relevant terms and concepts from Learn PAd, including an explanation about how we support learning during business processes, how processes are mapped to a Wiki representation and how knowledge workers are supported by and contribute to the Wiki to improve models and thus achieve organizational learning.

The Learn PAd project introduces a novel model-driven approach for workplace learning in the application domain of public administrations (PA) (Emmenegger et al. 2016). It creates a collaborative environment in the form of a Wiki to represent business processes and tasks, to recommend learning help (e.g. the contact details of experts, selection of similar and conventional learning material like books, audio and video files) and permits tips and advice to be contributed by writing experience reports (Pierantonio et al. 2015).

To model collaborative workplace learning centred on business processes and their context, we extended existing meta models, e.g. standard notations such as Business Process Model and Notation (BPMN) (OMG 2011) and Business Motivation Model (BMM) (OMG 2010) and created new ones, based on standards (e.g. the Competency Meta Model is deduced from the European Qualifications Framework (EQF) (European Commission, no date)). We then transformed the models and relations between them into an ontological representation for automatic reasoning and into Wiki pages and links for learning purposes. If a user (learner) logs in to the Learn PAd Wiki and accesses a page with a task description, based on context information (about the process the task belongs to and the user), appropriate learning help is determined and recommended to the learner. Thus, the Wiki is used to represent information to learners in a convenient way and the ontology is used to infer the necessary context information. As the Wiki is meant to encourage users to contribute their knowledge to improve business performance (Emmenegger et al., 2016) experience reports may become rather long, reflecting many different aspects. Over time, users will face the situation that although a recommended experience report is highly relevant, reading through all the provided information becomes too time-consuming. The same applies of course for other learning materials or, for example, regulations: Often only a small fraction of their content is really relevant to the task at hand. For this reason, the recommender was enhanced by another function to permit extraction or highlighting of specific sections of the report.

3 Related Work

Reduction of information overload in workplace learning can be achieved in several ways, some of which have already been well studied by other researchers.

For instance, much research has been done in the area of information retrieval, i.e. for scenarios in which a learner searches actively for missing information. In many adaptive information retrieval approaches, the increased relevance of search results is targeted via personalization techniques—the relevance of retrieved results may be (re-)assessed based on interests, tasks and previous knowledge of learners:

- *Individualization/personalization of search results* can be based on general user interests, which might be modeled in different ways (Gauch et al. 2007). Specifically, they might be derived either automatically, based on a user's behavior in previous search tasks (Morita and Shinoda 1994; Shen, Tan and Zhai 2005) or modeled explicitly as, for example, in (Hopfgartner and Jose 2014). There are also hybrid approaches that try to use explicitly modeled information about user preferences where possible, but fall back on implicit information when explicit information is unavailable (Fernández et al. 2011).
- *Context modeling* takes into account the fact that user interests are not generic, but may vary according to the context and task at hand. Thus, some approaches subdivide user profiles according to certain (search) tasks, thereby relying on models of the domain of discourse (Vallet *et al.* 2007; Mylonas et al. 2008). In Asfari et al. (2009), context is modeled explicitly as the task/activity that a user is performing.

Another aspect of information overload is the challenge of assessing the (probable) relevance of presented search results. Instead of forcing a searcher to access and read document content, a search engine can assist in this challenge via *query-biased document summaries*, which give a fast overview of the context in which query terms appear in a document. Computation of such summaries can be formulated as a sentence selection task and may rely on learning-to-rank approaches (Wang et al. 2007), classification (Metzler and Kanungo 2008) or on graph-based scoring of sentences based on sentence similarity graphs (Varadarajan and Hristidis 2006).

Instead of requiring a user to engage in active search activities, the *recommendation* of suitable information items aims at a proactive delivery of information to a user when that information is needed. In general, recommenders are often used in e-commerce where they aim at suggesting items/products to a user that might be of interest to that person. Recommenders can be based on *collaborative filtering* (Linden, Smith and York 2003), i.e. using the preferences of other users with similar interests. They can also be *content-based,* i.e. based on a comparison between user profile and content or description of the recommended items. Or they can be based on *association analyses* (Sarwar et al. 2000) that identify which items are often picked together and use that knowledge to suggest items to be added to an existing selection.

In the context of learning, recommenders have been proposed as part of *Adaptive Educational Systems (AES)* (Brusilovsky and Peylo 2003). Such systems aim at recommending to a learner which learning materials to consume next or which action to perform next (Zaíane 2002), based on the current level of knowledge, learning style/preferences (Peter, Bacon and Dastbaz 2009) and previous learning activities of that learner. More precisely, Hauger and Köck (2007) distinguish between *presentation support* on the one hand—additional explanations, based on what a learner already knows—and *navigation support* – recommending where to go next.

Hence, as proposed by (Alshammari, Anane and Hendley 2014), an AES needs to have a *Learner Model*, comprising information about the learner's knowledge and skills, current learning goal and preferred learning style, and a *Domain Model* that represents the real-world domain to be studied by students, used to annotate learning materials to match against the learner model. The learner model then permits *personalized* recommendations, i.e. make them relevant for the learner in terms of both suitable level of knowledge and preferred learning style (Dunn and Dunn 1978). In terms of skill level, good recommendations are in a student's *zone of proximal development* (Vygotsky 1978), i.e. they help the student to gain skills that are just above his or her current level, but can be reached with appropriate guidance. Personalization of learning has also been studied extensively, e.g. for recommendation of learning paths (Chen 2008; Hwang et al. 2010).

As in other domains (see above), recommendations can be based on content similarity (Ghauth and Abdullah 2010) or collaborative filtering (Khribi, Jemni and Nasraoui 2009).

Finally, there is (relatively little) work focusing on the recommendation of learning materials in workplace learning that considers the (current) work context of a learner. Notably, (Abecker et al. 2000), (Abecker et al. 1998) and (Schmidt and Winterhalter 2004) suggest that recommendations in workplace learning should be based on both the role and position of the user within the organization and on the (current) work context in terms of the task or process to be executed. Such information can be gained e.g. via the integration of information delivery with a workflow engine (Abecker et al. 2000). Another example of task-specific information delivery is provided by Ye and Fischer (2002), suggesting using the task context in a software development context to deliver relevant code to be reused in a programming task. In the Learn PAd project the learners' context, for example, their working environment, skills, experiences and personal preferences, were considered for recommendations (Emmenegger et al. 2016).

Overall, previous research on text summaries has focused on the search task. Proactive information delivery in workplace learning using task context for the production of short document summaries in a proactive information delivery approach has not been studied.

We address this research gap by designing a new solution for proactive, personalized and context-aware information delivery with "task-biased" text summarization.

4 Determining Information Relevance

In the following sections, we introduce the conceptual approach and describe the implementation. The methodology our research follows is design science research

(DSR) (Hevner et al. 2004). In order to elicit realistic requirements and to make sure that the solution is applicable in practice, we created an application scenario together with partners from the Learn PAd project that reflects a user's real working environment and illustrates role and output of the enhanced recommendation system.

4.1 Example Scenario

The example scenario we introduce is part of a larger scenario investigated within the Learn PAd project called "European Project Budget Reporting" (EPBR). EPBR refers to the activities that an Italian public research body (in reference to its administrative offices) has to carry out if it participates in a European research project. As the process is rather complicated, many recommendations are provided to support learners, e.g. novice users, in performing it. Based on answers gathered in semi-structured interviews during the awareness phase of DSR the Wiki page reporting learners' experience is considered the most vulnerable to the information flood, along with lengthy learning materials, such as (new) regulations.

We imagine a situation where a novice user who recently started work for an organization that is partner in an EU-project consortium is asked to do the periodic financial reporting. Although many helpful recommendations to support the administrative reporting activities are provided, the newcomer is overwhelmed by the information she or he finds in the Wiki pages and may also not be able to find the relevant sections in the provided learning materials, e.g. regulations. She or he would appreciate a (relevant) subset of the information according to her or his personal profile (e.g. with respect to skills, experiences, acquired knowledge in the domain, learning preferences) and the specific case at hand. To meet his or her needs, the Wiki pages should only display sections that match his or her profile and condense details to the most relevant facts.

4.2 Concept

In the context of our example scenario, we address two important forms of textual information items that are accessible from task-related Wiki pages:

- *Learning materials*: here, we refer to any items that contain information related to a task, and which may support a performer of that task in finding solutions and making appropriate decisions within the task. In other words, we understand the term "learning materials" in a very broad sense, and do not assume that the materials have a specific didactic purpose. They may take the form of e.g. explicit guidelines or background information such as law texts, regulations or interpretations of these. Fig. 1 shows an example of a (passage-segmented) EU regulation that is used as learning material.

Can part of the management tasks be performed by other beneficiaries?

Coordination tasks are part of the "management tasks"; however, "management tasks" include tasks beyond
tasks will be performed by other beneficiaries and they will be reimbursed at 100% provided they comply w
on financial statements). In certain cases (i.e. big projects) there could be in a project a beneficiary carrying

Can there be a scientific coordinator other than the Coordinator?

The coordinator in the GA is defined only by the tasks mentioned in Article II.2.3. Tasks related to the coor
is possible that this beneficiary in charge of the task of scientific coordination, may be internally (i.e. within
another beneficiary of the ECGA. It will not be considered as the project coordinator. The tasks of scientific
"research and technological development activities" (i.e. 50% /75% reimbursement rate). By their nature (sc

Example:

Beneficiary "B" is leader of Work Package I in Project X, and in charge of the publication of a competitive c
Packages of the project. He also has to provide a certificate on the financial statements.

Reimbursement rates:

- For its RTD work: 50% (75% if falling under the cases detailed in Article II.16.1.2 of ECGA)
- For its management work related to the competitive call within Work Package I: 100%
- For its scientific coordination of the project: 50/75% (as this is part of the RTD activities)
- For its management costs related to the certificate on financial statements: 100%

Can a financially weak legal entity be coordinator of a project?

Fig. 1 A (passage-segmented) EU regulation as a specific example of learning material

- *Experience pages*: Here, we refer to special Wiki pages that contain user-contributed experience in textual form, as shown in the example in Fig. 2.

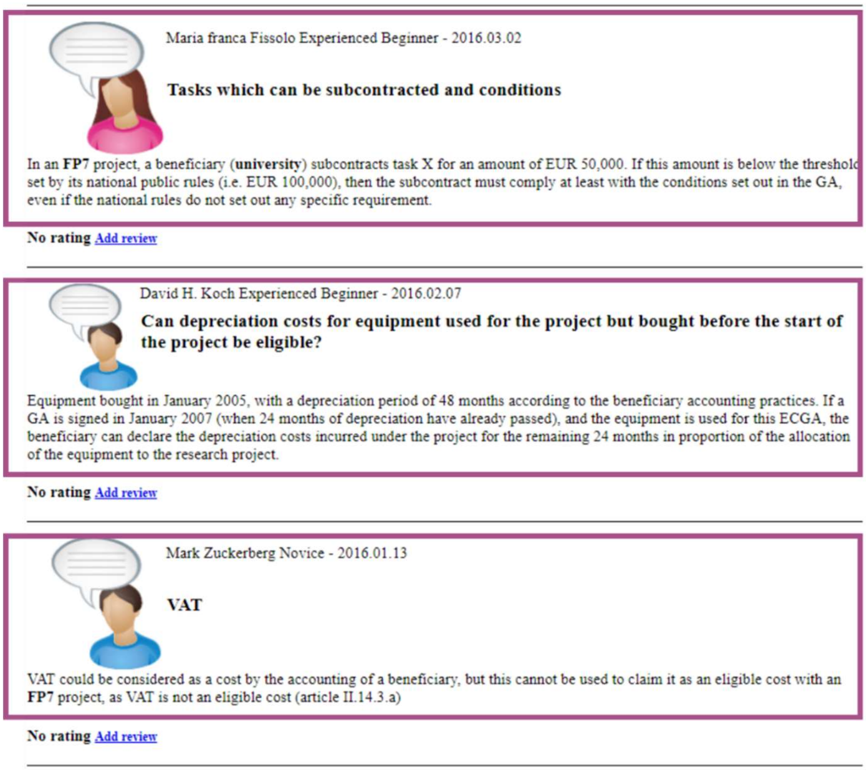

Fig. 2 Example of a user experience page

Dealing with information overload in such a context means relieving the user of the task of scanning vast amounts of contents of learning materials and/or experience pages, because information which satisfies a specific user's need is hidden in text that is not relevant within the specific situation.

We therefore propose filtering and summarizing the textual contents in order to highlight only those passages of text that are relevant in the context of a given task and that match the user's profile in terms of previous knowledge required and learning style.

To this end, we will construct a complex query which describes the user's task context and profile to improve the approach for building recommendations implemented in the Learn PAd project (Silingas et al. 2015).

More precisely, the query will be composed of

- Important keywords that are extracted from the title and description of the task at hand. This information is contained in the respective business process model and its corresponding Wiki page. The keywords will be used to bias text summaries towards the task context.
- Keywords extracted from the description of the case (i.e. process instance) the user is working on. This data is available from an integration with a workflow engine, which captures the case-specific data. In our example scenario, this might comprise, for example, the EU funding program or the country for which the financial report is made. The extracted keywords will help to make text summaries relevant to the particular case the user is working on.
- The acquired skills and preferred learning style of the learner (e.g. whether she or he learns better through visual or auditory stimuli etc., see (Dunn and Dunn 1978)). This information can be used to filter and rank results

such that the user primarily sees items that match the preferred learning style and that are appropriate in terms of his or her skill level – i.e. leading to a level of knowledge that is just above the user's current level (see (Emmenegger et al. 2016)).

Obviously, our resulting approach is hybrid, being based on keywords to describe the task context and the explicit ontology-based modeling for user profiles. The next section describes in more detail how the queries are constructed and processed.

4.3 Implementation

Next, we present our algorithm *TBPTSL—task-biased and personalized text summarization for learning*.

As a starting point, we build on the Learn PAd approach in which a business process such as the one from our example scenario was modeled and this model was then translated into a series of Wiki pages that contain titles, descriptions and other attributes of model elements (e.g. tasks) (De Angelis et al. 2015). Furthermore, we assume that learning materials were attached to some of the Wiki pages and that users contributed their experiences to some of the tasks of the process in textual form on the experience pages.

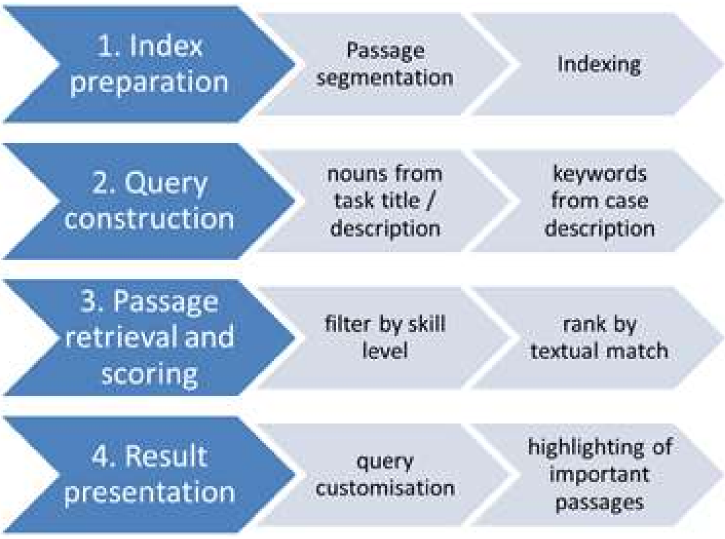

Fig. 3 Overview of the TBPTSL algorithm

Fig. 3 shows an overview of the algorithm which we will explain in detail here:

Step 1: Index preparation: Before proactive information delivery can start, it is prepared by segmenting learning materials and experience page contents into passages and creating an index for these.

After the index has been prepared, the system is ready to support a user working on a case (i.e. a process instance), in our case, preparing a report for the EU Commission. The user enters the case data and is then taken through the various tasks of the process on the Wiki pages. Let us assume now that the user is working on a particular task within the process and has navigated to the corresponding page in the Wiki.

Fig. *4* shows such a situation: The user is working on the task "Calculate direct cost" and sees a short description of that task, including recommended subtasks, a link to the experiences that other users contributed, at the bottom of the page. On the right hand side, the "Process Context" pane contains information about the current process instance, namely details of the project for which the financial report has to be created.

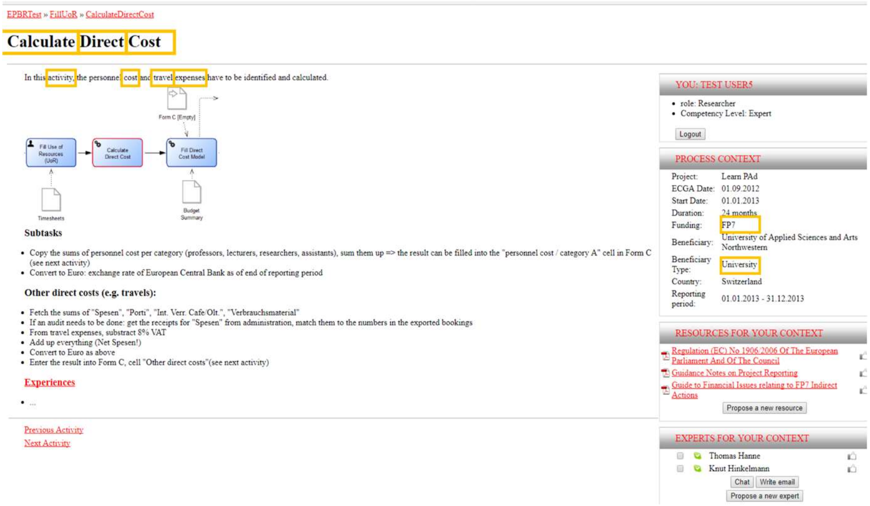

Fig. 4 Screenshot of a Wiki page representing a task and a case context in the Learn PAd Wiki

Step 2: Query construction: In this phase, the query will be constructed as described in the previous section, i.e. by extracting nouns from the title and description fields of the task elements, by capturing keywords from the description of the current case (e.g. "FP7" in the example of Figure 4) and by forwarding the skill level of the user to the system. In our initial implementation, we did not consider the preferred learning style of the user; this will be the subject of future work. The yellow boxes in Figure 4 show which keywords are extracted in that particular example. Note that information about skills, preferences, etc. is captured as part of the Learn PAd project.

Step 3: Passage retrieval and scoring: Next, the indexed passages are now retrieved and ranked. Based on the keywords of the query, a ranking of passages is performed using the BM25 retrieval function (Robertson and Walker 1994). Then the results are filtered: Especially for user-contributed content, only contributions of other users with a skill level equal to or higher than that of the current user will be retained.

Step 4: Result presentation: Finally, the results are presented as shown in Figure 5 (note that due to lack of space the lower section of the result page is shown on the right side of the figure): In the upper section, snippets of the most relevant passages can be seen. A learner may check in this section whether relevant suggestions are available and navigate to these passages directly. The user can also customize the query by either adding (see orange box above the snippet) or removing keywords (orange box below the snippets). Finally, when scrolling down, the user sees the original content of the page—in this case user-contributed experiences—where passages are highlighted that were ranked highly in step 3. Thus, the user sees the passages in their original context, but can scan the document much faster by focusing only on the parts that are relevant in the current task and case context.

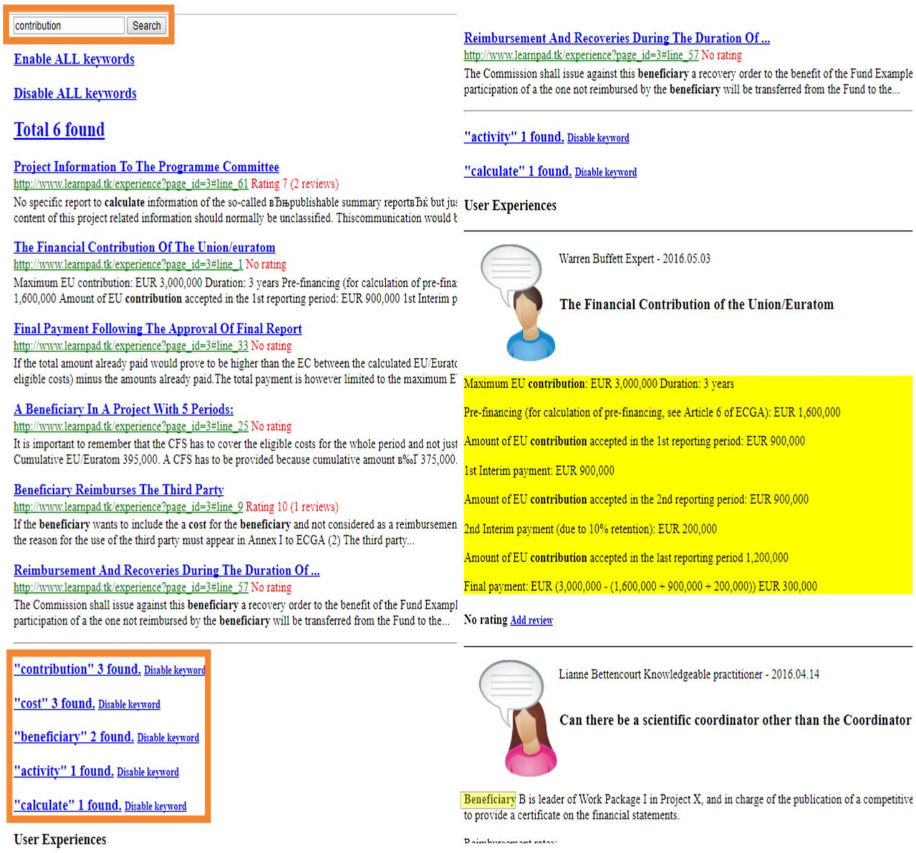

Fig. 5 Presentation of search results

5 Evaluation

5.1 Experimental Setup

In order to assess the usefulness of our proposed approach, we designed a small-scale experiment as follows:

1. We recruited four test persons who were vaguely familiar with the European Project Budget Reporting (EPBR) process.
2. We prepared a task to be performed by test persons within the context of the EPBR process. The task consisted of six subtasks (issues) that had to be performed as part of the tasks "Calculate direct cost" and "Calculate indirect cost"—issues typically consisted of deciding about the eligibility of certain costs or of computing costs, according to the EU guidelines. These tasks had to be performed for a (partially fictitious) research project case that we constructed.
3. We prepared a testbed in which extensive information was provided in the form of user-contributed experiences (which we extracted from the EU guidelines). The content covered many more topics than were needed to solve the six issues—i.e. the problem of information overload was present in this scenario. In the testbed, the functionality of our TBPTSL algorithm—as described in the previous sections—could be switched on or off.
4. We then had each participant perform three of the six tasks without the help of TBPTSL, i.e. just using the standard search functionalities of a web browser. The other three tasks could be solved using the full functionality

of the TBPTSL algorithm. In order to reduce the "person bias" given by the different previous knowledge of the participants, we let the first two participants solve issues 1, 2 and 3 with TBPTSL and 4, 5 and 6 without it. For the other two participants, we reversed the order so that they started with issues 1, 2 and 3 without TBPTSL and then worked on issues 4, 5 and 6 with TBPTSL.

5. We asked all participants to try to solve the issues as quickly and accurately as possible; we then measured the time they needed to do so.

After completion of the tasks, we asked the participants about their subjective judgment of the TBPTSL functionalities using the following interview questions:

- In your opinion, does TBPTSL help you find the required information faster?
- In your opinion, does TBPTSL help you deal with information overload?
- Which changes would you suggest to improve TBPTSL?

5.2 Results

Table 1shows the time needed by each test person for each issue. In the table, green cells represent an issue that was solved with the help of TBPTSL, whereas red cells stand for *not using TBPTSL*.

Issue	TP1	TP2	TP3	TP4
1	4	20	2	5
2	3	15	4	3
3	3	10	6	5
4	5	15	4	1
5	4	15	3	1
6	6	15	4	7

Table 1 Time needed by test persons to solve the 6 issues

We collected all answers to the interview questions and coded them manually. The results are as follows:

- Regarding the first question, there is no clear opinion among participants: Three of them agreed that it was hard to tell, two attributed this to the great variation in task difficulty ("it depends on the task") and one stated that the tasks were too easy to really notice a difference. Another participant also confirmed this, and claimed that for easy tasks the standard browser search functionality is sufficient. It should be noted though that in this context, an easy task is not one that is easily explained but one that can be searched for by using only one or two important keywords. In any case, these answers are quite consistent with the measured time for task completion.
- For the second question, there was total agreement among participants: All four stated that they believed that TBPTSL would help to reduce information overload. This indicates that participants see a potential for TBPTSL beyond the (rather easy) tasks that they performed.
- Lastly, each participant suggested a concrete improvement that was different from that the suggestion of the other participants. However, all suggestions had something to do with advanced information retrieval techniques: Participants proposed including phrases in the search (and hence index), to use stemming and to allow user ratings of contents and use them for ranking. We implemented all of these suggestions into our final solution. A last suggestion was to consider term semantics—which would

require the use of a thesaurus or similar, but which we have not (yet) implemented.

It is obviously difficult to conclude much from the figures in Table 1 although the average time needed to solve issues with TBPTSL (all green cells, 6.25 minutes) is less than that of solving them without TBPTSL (all red cells, 7.08 minutes), the difference is not significant. This is of course due to the small sample size. In addition, there were other sources of variation that we could not fully control: The difficulty of the tasks is of course not completely comparable, neither is the prior knowledge of the participants. Therefore, more investigation will be needed to confirm the positive effect of TBPTSL in quantitative terms.

6 Conclusions and Future Work

Experiences reported in Wiki pages are a helpful instrument for learners who seek support for the execution of a (complex) business activity. However, when the Wiki is used a great deal, information/experience reports may become rather long and confusing and pages with explanations may become very detailed. What is commonly known as information flood can also be considered in this context. Therefore, it is not enough to recommend appropriate (Wiki) pages; the text also has to be extracted and summarized according to the user's/learner's profile. With our approach, we were able to show how recommendations for workplace learning can be improved by applying appropriate filters to text passages (in Wiki pages) based on task context and personal information. As we already represent background information in an ontology (a user's working context, e.g. the business activity she or he is about to execute, the organization structure of his or her organization) and his or her personal profile, we can enhance it by adding information about recommendations 'liked' by the user If, for example, a learner 'likes' contributions of a certain author more than of others, learning material related to this author might be recommended first. Hence, a promising thread in future work could be to analyze users'/learners' opinions of and experiences with learning material and use them to further improve recommendations, respectively filter recommended information.

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