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CONF-IRM 2018 Proceedings

International Conference on Information Resources Management (CONF-IRM)

5-2018

A Personalized Knowledge Recommender System For Workspace Learning

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Abstract:

Technology Enhanced Learning (TEL) is emerging as a popular learning approach utilized by both educational institutions and business organizations. Learning Recommender Systems (RSs) can help e-learners to cope with the data overload difficulty and suggest useful items that users may wish to use. This research aims to examine the design and implementation of personalized RS that supports individual learning in the workplace. First, a hybrid knowledge recommendation technique is proposed by combing content-based method with feedback learning method to adapt to the dynamic preference of users. Second, the design and implementation of a personalized knowledge recommender system using proposed technique in a case company is presented. Quantitative and qualitative data are collected to validate the system and evaluate its performance and impact. The preliminary results show that involving enterprise experts and target users in the system design phase can improve the system transparency and users' trust in the system. It is also found that users' learning attitude can be positively influenced by the system experience. This research provides important implications on employing intelligent recommender system to support workplace learning.

Keywords:

Recommender system, workplace learning, learning attitude

1. Introduction

Recommender Systems (RSs) can be described as systems that guides users in a personalized way to make decisions on choices for certain predefined purpose. Successful deployments of recommendation systems in e-commerce have led to the development of recommenders in new application domains. With the increasing popularity of Technology Enhanced Learning (TEL) in educational establishments, the e-learning RSs have been growing rapidly in the past few decades (Lu, 2004). Learning in the organizational context is usually not modularized and each learner has different scenarios or needs that stimulate personal learning. TEL provides the opportunities to lifelong learning at the workplace of manufacturing companies. Chinese manufacturing industry contributes significantly to many countries' economy. However, to become more than just a "factory of the world", Chinese manufacturing companies need to align workplace learning with organizational learning with support from TEL.

E-learning RSs try to filter content for different learning objectives and settings. Although there is a large number of RSs that have been deployed in TEL settings, the alignment of workplace learning with organization knowledge development need has been overlooked. The efficacy of RSs is said to strongly depend on the context or domain they operate in (Drachsler, Hummel & Koper, 2008). This empirical study investigates the design requirements, evaluation method, and impacts of RSs for workplace learning in the context of OL and Chinese manufacturing industry.

The content of this paper is organized as follows. The next section reports related work. Section 3 presents our research methodology. Section 4 describes the proposed recommendation technique and architecture of RS. The following section reports the implementation of proposed RS in the case company. Section 6 is composed of data analysis and results discussion. We conclude with the contributions, limitations and future directions of this research.

2. Related Work

Relevant research of this study comprises of recommendation techniques, RS in the e-learning environment, RS for workplace learning and performance evaluation of educational RSs. This section discusses the related work and the research gaps.

2.1 Recommendation techniques

Recommendation techniques are core to RSs as it determines the classification and performance of RSs. Content-based recommendation technique is one the most popular techniques used by knowledge RS. Content-based RSs utilize item information as item features to rank items according to their similarity to user's interest preference (Hill, Stead, Rosenstein et al., 1995). Content-based recommendation technique can be combined with machine learning techniques. For example, Zuo & Zeng (2016) used deep neural networks to extract latent features from user profile tags and built user model with lower dimensionality. Content-based method does not reply on the user historic ratings on the items, but requires large amount of user profile information and item information to calculate the matching results.

2.2 RS for Workplace Learning

Personalized e-learning has been researched extensively due to the rapid increase of digital learning resources. Learning activities at the workplace involve both formal and informal learning (Drachsler, Hummel & Koper, 2008). Kooken, Ley & Hoog (2007) confirmed that people do learn during work frequently, and their learning is mainly driven by the work people are doing. Personalized e-learning RSs for workplace learning are expected to meet the dynamic learning needs and serve organization's knowledge development requests. To link individual needs with organizational interest, Jia, Wang, Ran et al. (2011) used a performance based approach and ontology workplace e-learning system. Zhen, Huang & Jiang (2010) proposed a model of inner-enterprise knowledge RS based on the semantic matching of context information from both users' and knowledge's side. Moreira & Souza (2016) designed a content-based RS that recommends posts and topics to company employees and board.

2.4 Recommender System Performance Evaluation

Objective measures like error and accuracy are commonly discussed and used to evaluate performance of recommendation algorithm. However, performance of recommendation algorithm may not always correlate with how the users perceive the value of an RS (Pu, Chen & Hu, 2011). Other system aspects should be measured, and in particular, those related to the acceptance of recommendations (Cremonesi, Garzotto & Turrin, 2012). The relevance, transparency, the way that preferences are elicited influence the perceptions of credibility and the acceptance of a recommendation (Gretzel, Fesenmaier, Formica et al., 2006). Pu, Chen & Hu (2011) assessed the qualities of RSs in four dimensions: 1) user perceived qualities, 2) user beliefs, 3) user subjective attitudes, 4) user behavioral intentions.

2.5 Research Gaps

Most of the existing studies on personalized RS can not adequately cope with the dynamic preference of users in the workplace which is job task oriented. There is also a need to link personal learning with organization knowledge development need. Impact of using knowledge RS on learner's cognitive attribute remains unexplored. This research proposed a hybrid approach that combined content-based method and feedback learning method to adapt to dynamic user need. The system impact on user's learning attitude is also examined.

3. Research Methodology

In this research, we proposed a hybrid recommendation technique in the design of a knowledge RS for workplace learning in the context of Chinese manufacturing industry. To validate the proposed RS and investigate its impact on users' learning attitude, we implemented the system in a case manufacturing company. Quantitative data was collected for hypothesis testing and system performance evaluation.

3.1 Hypotheses on user learning attitude

Learning in the organizational context is not an isolated activity but influenced by various contextual factors. Understanding the influence of knowledge RS on employees' attitude can provide further insight into how to leverage information technologies to initiate individual behavioral change toward the organizational benefit. The learning attitude and knowledge sharing are found to be influenced by organizational culture, information communication technology (ICT), project management methodology (Schindler & Eppler, 2003). Therefore, we investigated the change of user learning attitude and willingness of knowledge sharing. In this regard, we put forward our hypotheses:

H1. There is a difference in user learning attitude before and after using the knowledge RS.

H2. There is a difference in knowledge sharing willingness before and after using the knowledge RS.

3.2 Survey Instrument

A questionnaire was designed to collect quantitative data about user learning motivation and willingness of sharing knowledge (as shown in Table 1). Users were asked to indicate their answers to each of the questions using the 1-6 Likert scales, where 1 indicates "strongly disagree" and 6 is "strongly agree". This questionnaire was administered at the beginning and the end of experiment. Paired t-test was performed on each measurement factor to test our hypotheses.

Questions	**Reference**
Learning attitude	Geng, Chuah &
LA1) I hope to receive and learn new knowledge	Cheung, 2016; Swart,
LA2) My positive learning attitude will help me perform better in working	Kinnie, Rossenberg et
Knowledge sharing	al., 2014;
KS1) I learn a lot new skills by asking colleagues in the company	Wilkesmann, Fischer
KS2) Others colleagues support my efforts to gain work experience	& Wilkesmann, 2009

Table 1: Questionnaire about the user attitude

3.3 System performance evaluation

We evaluate the system performance in terms of the user experience and eight features are included in the evaluation survey: Accuracy, Novelty, Interpretable presentations, Perceived usefulness, Ease of use, Transparency, Trust, and Global satisfaction. The evaluation results can help the designers to reflect on the design process and identify the critical features for the system quality in this new application context. There are 22 survey questions in total under the eight features. Users were asked to indicate their answers to each of the questions using the 1-6 Likert scales, where 1 indicates "strongly disagree" and 6 is "strongly agree".

4. Proposed Personalized Knowledge RS

The proposed personalized knowledge RS is named Personal Learning Assistant based on RS (PLARS). Figure 1 shows the system architecture of PLARS. The recommending process consists of four steps as explained in the following:

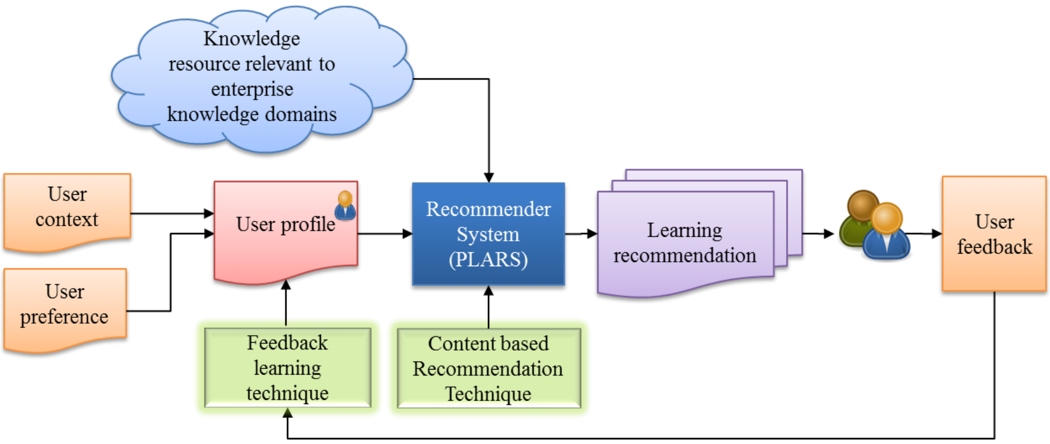

Fig 1: Architecture of proposed knowledge RS PLARS

Step 1 Knowledge resource identification

Knowledge resource plays a determinant role in maintaining the credibility and persuasiveness of knowledge RSs. There are mainly two types of knowledge resource: enterprise knowledge based system, and external knowledge provider. Enterprise knowledge based system stores various types of inner-enterprise knowledge such as operation instructions. External knowledge providers usually provide modularized learning material with predefined topics and scope. Using external knowledge resource for workplace learning requires the verification of its relevance to enterprise knowledge and examination of the content quality.

Step 2 User preference elicitation

To design an effective RS in e-learning environments, it is important to understand specific learners' characteristics desired in an RS such as learner's prior knowledge (Drachsler, Hummel & Koper, 2008; Sicilia, García-Barriocanal, Sánchez-Alonso et al., 2010). User profiles can contain users' demographic information, the ratings of purchased items, and contextual information. Users can also explicitly define their own interest preferences. Considering the lack of user ratings data at the initial stage, we let users to explicitly define their own preference first. Besides the user preference, PLARS also includes user's job functions as contextual factor to describe the user's job need. By adopting feedback learning method, user profiles can be continuously enriched by users' feedbacks on the recommended content.

Users' descriptions of their interest should be in the "same language" as the knowledge residing in the enterprise. Therefore, we used a predesigned ontology to standardize the categories of enterprise knowledge and asked users to elicit their preferences and job functions using these categories. In this way, the initial user profile is composed of a set of equal weighted categories of enterprise knowledge.

Step 3 Learning material retrieval

The retrieval of learning material from the knowledge repository uses content-based method that calculates the similarity between the user profile and learning material. In the retrieval process, we treat the set of categories as query input with a set of equal weighted terms. We adopted the BM25F scoring algorithm and incorporated the term weight in the calculation function as shown in equation (1), with default settings of b=0.75, k=1.50, to calculate the similarity score. The term weights are equal at the initial stage and gradually updated in the feedback learning stage. Higher similarity scores indicate better matching between documents and user preference.

$$score(D,Q) = \sum_{i=1}^{n} w_i \cdot IDF(q_i) \cdot \frac{f(q_i,D)\cdot(k_1+1)}{f(q_i,D)+k_1\cdot(1-b+b\cdot\frac{|D|}{avgdl})} \tag{1}$$

where
D= the learning document
Q= the set of terms in user profile
w_i= weight of term i in Q
q_i= term i in Q
IDF(q_i)= inverse document frequency of term i
f(q_i,D)= frequency of term i in document D
k_1= smoothing parameter
b= smoothing parameter
|D|= length of document D

Step 4 User feedback learning

User feedback is used to update the user profile by a feedback learning method. The interaction between user and RS follows a four-stage e-learning lifecycle that includes: 1) Self-evaluation, 2) Specify learning intention, 3) Select learning activities, 4) Learning action. The completion of each learning cycle is treated as a round of learning. The proposed knowledge RS generates learning recommendations in each round of learning. This four-stage lifecycle was used to illustrate how the system works for users and managers, thus to increase the transparency of the system. In each learning round, the user profiles are updated by adjusting the weights of features based on user scores on the learning content. This is realized by two steps:

Step1: $$\theta_i^k = \beta \cdot \frac{r}{s} \cdot \frac{sim(t_i,D^k)}{\sum sim(t_i,D^k)} + w_i^k \tag{2}$$

Step 2: $$w_i^{k+1} = \frac{\theta_i^k}{\sum \theta_i^k} \tag{3}$$

Where
$w_i^k =$ weight of term i before the k^{th} document or D^k has been rated by the user
$\theta_i^k =$ parameter corresponding to term i and the k^{th} document
$\beta =$ weight of the updating information $\frac{r}{s} \cdot \frac{sim(t_i,D)}{\sum sim(t_i,D)}$
$r =$ user rating for k^{th} document
$s =$ scale of rating (here is 5)
t_i = term i in the user profile
$D^k = k^{th}$ document recommended to the user
$sim(t_i, D^k) =$ similarity between term i and document D^k
$w_i^{k+1} =$ weight of term i after updating the score of D^k

The similarity between term i and document D^k is calculated by the same equation as $score(D, Q)$ introduced in Step 3. An example is provided here to illustrate the weight updating process. Suppose a user profile is $Q = \{t_1 = production\ planning, t_2 = cost\ control, t_3 = inventory\ management\}$. The corresponding weight of each term before updating the user rating on the first document is $W = \{w_1 = 1/3, w_2 = 1/3, w_3 = 1/3\}$. In the first round of recommendation, document D "Supply chain planning and control" is the first document recommended to this user and it receives a score of 4 out of 5 for user feedback. Therefore, $s = 5, r = 4\ and\ k = 1$. Here we assign 0.3 to the value of β as the weight of the updating information artificially. The θ value for each term after first step calculation is:

$$\theta_1^1 = 0.420,\ \theta_2^1 = 0.393, \theta_3^1 = 0.428$$

The term weights after feedback updating are:

$$w_1^2 = 0.338, w_2^2 = 0.317, w_3^2 = 0.345$$

It shows that the third term ($t_3 = inventory\ management$) received more weight than other terms because it has higher similarity score with the first document. Suppose a second document received a score of 1 out of 5, which is much lower than the first document, the weight increase on the most similar term will also be lower than the weight increase caused by the first document. Therefore, the more popular document leads to a larger increase in the term weight. In each round, more than one document can be suggested to users and the user profile can be updated multiple times. The updated user profile will be used in the next round to generate recommendations.

5. Case implementation and data collection

5.1 System implementation

To validate the PLARS in real enterprise scenarios, we selected an electronic component manufacturing company located in Dongguan, South China as our case site to implement experiment. The case company manufactures high volume precision photo-chemical etching parts for components of the hard disk drive industry. At the time of this study, this company has already adopted the organizational learning as one of their long-term development strategies. We invited employees from multiple functional departments to participate in the experiment as system users. A pilot study was carried out first to collect user interests and preferences. We also explained to participants how the RS works using the user system interaction process diagram.

PLARS employed a mixture of internal knowledge resource and external knowledge resource under the supervision of domain knowledge experts. The relevance and quality of learning material were verified to make sure recommended contents are relevant to users' working scenarios. Most of the learning materials are of consistent length containing both textual and graphical contents. PLARS was set to send recommendations to users in each learning cycle and the duration of each cycle is set to be one week considering the users' workload and time schedule. Users were asked to rate the learning recommendation using 1-5 Likert scales, where 1 indicates "not satisfied at all" and 5 is "very satisfied".

5.2 Data Collection

A total of 32 managers (with engineering background) and engineers were invited to be our system users and 2 participants dropped out. The experiment duration was two and a half months. Quantitative data related to user learning attitude were collected in two batch of surveys, one at the beginning and one at the end of experiment. The questionnaire presented in Table I was used. The system performance evaluation survey was administered at the end the experiment.

6. Data Analysis and Discussion

6.1 Effect of age, education, gender, and functional department

One-way ANOVA was performed to test the effect of age, education, gender, and functional department on the measurement factors (LA1, LA2, KS1, KS2) respectively. The results indicated that age, education, gender, functional department do not lead to any significant difference in user learning attitude or knowledge sharing willingness.

6.2 User Learning Attitude

This section discusses the influence of using knowledge RS on users' learning attitude and knowledge sharing willingness. As shown in Figure 2, an increase of score can be observed in learning attitude (LA1), perceived importance of learning (LA2), and knowledge sharing practice (KS1). The change in knowledge sharing environmental support (KS2) is not obviously shown.

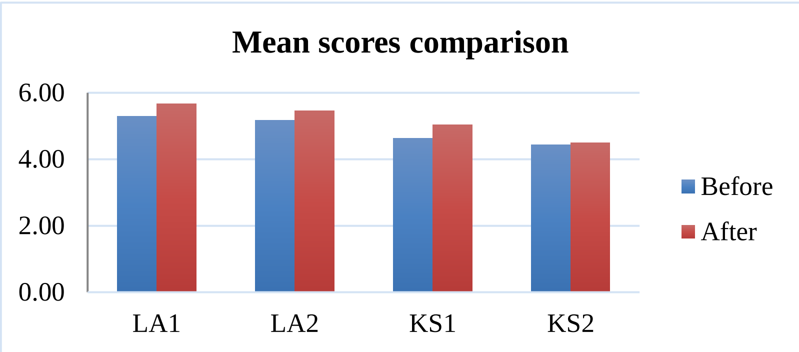

Fig 2: Mean scores of factors before and after using PLARS

6.2.1 Paired t-test results

We combined the score of LA1 and LA2 and used the average to denote the score of learning attitude. Paired t-test results showed that there was a significant increase in the score learning attitude ($t(29)=-2.226, p=0.034$) (Table 2) at a significance level of 0.05, which supported our hypothesis H1. This indicates that users are more willing to receive new knowledge and are more cognitively aware of the importance of learning with regard to their work performance after receiving recommendations from PLARS in the experiment.

We combined the score of KS1 and KIS2 and used the average to denote the score of knowledge sharing willingness. Paired t-test results showed that there was no significant increase in the score for knowledge sharing willingness ($t(29)=-1.701, p=0.100$) (Table 2) at a significance level of 0.05, which did not support our hypothesis H2. An interpretation of the result is that knowledge sharing happens at the interactions between people either online or offline. It involves both the information acquiring and disseminating processes. The PLARS provides support mainly for the information acquiring and does not contribute the information disseminating or interactions between people at the workplace.

Paired Samples Test						
	Paired Differences			t	df	Sig. (2-tailed)
After - Before	Mean diff	Std. Deviation	Std. Error Mean			
LA	0.30	0.74	0.13	2.23	29	0.03
KS	0.23	0.75	0.14	1.70	29	0.10

Table 2: Paired t-test results of learning attributes and knowledge sharing willingness

Hypotheses testing results implied that the PLARS has observable influence on people's learning attitude in the Chinese manufacturing company settings where organizational learning receives managerial support. It also suggested that other information communication platforms are needed to complement the knowledge recommendation service in facilitating the bidirectional knowledge sharing activities.

6.3 System performance evaluation

We evaluated the system performance in terms of eight performance dimensions: Accuracy, Novelty, Interpretable presentations, Perceived usefulness, Ease of use, Transparency, Trust, and Global satisfaction. An overview of mean user scores of these eight performance criteria is presented in Figure 3.

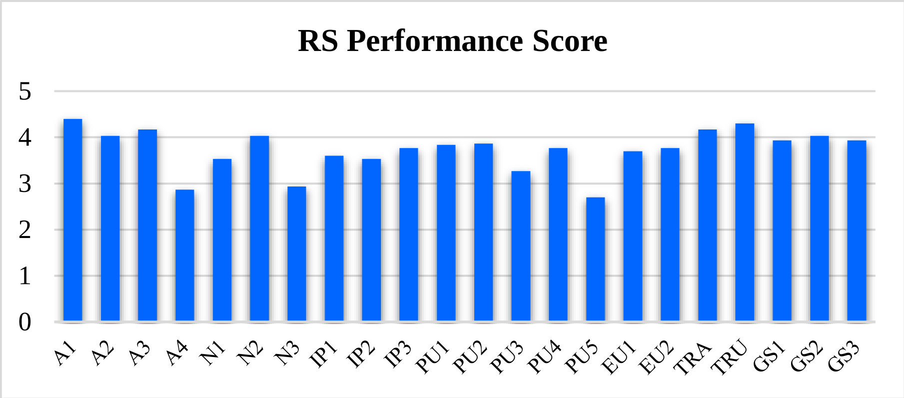

Fig 3: Mean user scores for system performance measures

Except for questions whose score negatively associated with system performance, most of the other questions received satisfactory scores with an average of 3.88. 'Accuracy' and 'Trust' received relatively higher scores than other performance criteria. 'Accuracy' measures how well users think the recommendations fit with the user interest preference, which tells more about the performance of recommendation algorithm. The score of 'Trust' reflects the users' perception of the credibility of recommended material. These evaluation results implied that the proposed recommendation technique worked effectively in generating appropriate recommendations based on user preference. In the design of PLARS, we involved the experts to select the knowledge source and judge the quality of learning material. In the pilot study, we used the e-learning lifecycle to explain how our system works toward users. This improves the transparency of system functionality and explains the good system performance in terms of “Trust”. The ‘perceived usefulness’ received relatively lower score than other measurement aspects. This indicates that the user job functions in the user profiles is not sufficient to characterize the dynamic user working scenarios. More specific elicitation of job tasks and more advanced feedback collection designs are required to cope with the dynamic need of users.

7. Conclusions, limitations, and future directions

This study examined the design and implementation of a personalized knowledge RS, PLARS, for workplace learning in the Chinese manufacturing industry. A hybrid recommendation technique that combines the content-based method and feedback learning method is proposed. User job task information and learning feedbacks are used to create and update user profile to adapt to the dynamic user learning preferences. Case implementation of PLARS validated the system design and illustrated the effectiveness of proposed recommendation technique. Moreover, it is found that successful implementation of RS in the organizations relies on management support, IT professionalism, and user commitment. Involving managers, domain experts, and users in the system design process can improve the system credibility and users’ trust in the system. The use of knowledge RS has a positive influence on the user’s learning attitude. However, it does not contribute to enhancing the knowledge sharing willingness of users. This research provides important academic and practical implications on the design and implementation of personalized knowledge RS in the context of manufacturing industry.

There are also limitations in this study that help drive future research. First, one-dimension user feedback neglects other criteria of knowledge type information resource. A multi-dimensional feedback collection method can better reflect user perceptions and preferences. Second, larger scale of implementation within multiple industry sectors can provide more insights about future improvement of RS for workplace learning.

References

Cremonesi, P. Garzotto, F. & Turrin, R. (2012). Investigating the persuasion potential of recommender systems from a quality perspective: An empirical study. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, *2*(2), 11.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

Drachsler, H. Hummel, H. G. & Koper, R. (2008). Personal recommender systems for learners in lifelong learning networks: the requirements, techniques and model. *International Journal of Learning Technology*, 3(4), 404-423.

Geng, G. S., Chuah, K. B., & Cheung, C. K. (2016). Learning and knowledge sharing in a manufacturing company. *Knowledge Management*, *16*(4), 13-32.

Gretzel, U. Fesenmaier, D. R. Formica, S. & O'Leary, J. T. (2006). Searching for the future: Challenges faced by destination marketing organizations. *Journal of Travel Research*, *45*(2), 116-126.

Hill, W. Stead, L. (1995). Rosenstein M, et al. Recommending and evaluating choices in a virtual community of use. *Sigchi Conference on Human Factors in Computing Systems,* 194-201.

Jia, H. Wang, M. Ran, W. Yang, S. J. Liao, J. & Chiu, D. K. (2011). Design of a performance-oriented workplace e-learning system using ontology. *Expert Systems with Applications*, *38*(4), 3372-3382.

Karaali, D. Gumussoy, C. A. & Calisir, F. (2011). Factors affecting the intention to use a web-based learning system among blue-collar workers in the automotive industry. Computers in Human Behavior, 27(1), 343-354.

Kooken, J. Ley, T. & De Hoog, R. (2007). How do people learn at the workplace? investigating four workplace learning assumptions. In *European Conference on Technology Enhanced Learning*, 158-171. Springer, Berlin, Heidelberg.

Lu, J. (2004). A personalized e-learning material recommender system. In *International Conference on Information Technology and Applications*. Macquarie Scientific Publishing.

Michlík, P. & Bieliková, M. (2010). Exercises recommending for limited time learning. *Procedia Computer Science*, *1*(2), 2821-2828.

Moreira, G. D. S. P., & Souza G. A. (2016). Recommender system to tackle enterprise collaboration. *ACM Conference on Recommender Systems. ACM,* 395-396.

Pu, P. Chen, L. & Hu, R. (2011). A user-centric evaluation framework for recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems,* 157-164. ACM.

Schindler, M. & Eppler, M. J. (2003). Harvesting project knowledge: a review of project learning methods and success factors. *International Journal of Project Management*, *21*(3), 219-228.

Sicilia, M. Á. García-Barriocanal, E. Sánchez-Alonso, S. & Cechinel, C. (2010). Exploring user-based recommender results in large learning object repositories: the case of MERLOT. *Procedia Computer Science*, *1*(2), 2859-2864.

Swart, J. Kinnie, N. Rossenberg, Y. & Yalabik, Z. Y. (2014). Why should I share my knowledge? A multiple foci of commitment perspective. *Human Resource Management Journal*, *24*(3), 269-289.

Wood, R. & Bandura, A. (1989). Social cognitive theory of organizational management. *Academy of Management Review*, *14*(3), 361-384.

Wilkesmann, U. Fischer, H. & Wilkesmann, M. (2009). Cultural characteristics of knowledge transfer. *Journal of Knowledge Management*, *13*(6), 464-477.

Yoo, K. H. & Gretzel, U. (2011). Creating more credible and persuasive recommender systems: The influence of source characteristics on recommender system evaluations. In *Recommender Systems Handbook*, 455-477. Springer US.

Zhen, L. Huang, G. Q. & Jiang, Z. (2010). An inner-enterprise knowledge recommender system. *Expert Systems with Applications*, *37*(2), 1703-1712.

Zuo, Y. Zeng, J. Gong, M. & Jiao, L. (2016). Tag-aware recommender systems based on deep neural networks. *Neurocomputing*, *204*, 51-60.