

# **Exploring social recommenders for teacher networks to address challenges of starting teachers**

*Soude Fazeli, Francis Brouns, Hendrik Drachsler, Peter Sloep*

*Open Universiteit of the Netherlands, Centre for Learning Sciences and Technologies,  
[soude.fazeli@ou.nl](mailto:soude.fazeli@ou.nl), [francis.brouns@ou.nl](mailto:francis.brouns@ou.nl), [hendrik.drachsler@ou.nl](mailto:hendrik.drachsler@ou.nl), [peter.sloep@ou.nl](mailto:peter.sloep@ou.nl)*

## **Abstract**

The lack of a proper induction and organizational socialization is seen as one of the main reasons for beginning employees to leave the profession after a few years. It seems especially problematic for professions such as teaching. Teachers work in contexts that do not allow frequent and intense observations and interaction with others who could provide meaningful information and act as exemplars of good practice. Recently graduated teachers experience their first job as extremely challenging and they typically lack social support during their induction period. Teachers look for mentors and colleagues they can trust and discuss their problems with rather than content expert. Comprehensive induction programmes are characterised by accessing to good mentors, having relationships to and with peers, and professional development. Learning Networks, as online social networks designed to support professional development can fill this gap by offering an informal social support structure for professional development. They can improve the quality of the induction of starting teachers by providing means to share, exchange and acquire knowledge and experiences with other teachers. Not only can teachers find resources, moreover they get access to like-minded people with expertise and experience in the same domain. However, providing opportunities to meet like-minded people does not automatically result in the required social interactions for knowledge sharing. Therefore, we propose in this paper a social recommender that assists young teachers to find most suitable peers to address their problems. The social recommender is inspired by recommender systems from the e-commerce world that recommend most suitable content to a user. In this paper, we first analyse the problems that young teachers face during their induction phase. Second, we present online Learning Networks as a promising solution for the induction phase of starting teachers. Third, we evaluate promising recommendation approaches for the intended social recommender within the Learning Network, and we present some initial ideas on how to improve them to take into account the learner characteristics and also to meet the conditions of a Learning Network. Finally, we present a model and draw further conclusions for design and implementation of the Learning Network and the social recommender for starting teachers.

## **Keywords**

starting teachers, induction, Learning Network, Recommender system

## **Introduction**

Starting teachers often encounter numerous challenges during their first few years of teaching (so-called induction period). Although several of these challenges are related to subject and pedagogical related issues such as classroom management, socialization of starting teachers in terms of meaningful interaction between starting teachers and both their schools and the 'external world' (such as parents) constitutes a major proportion of these challenges (Kelchtermans & Ballet, 2002). Starting teachers often suffer from isolation emotionally when they are assigned to classrooms that are isolated physically. On the one hand, they themselves usually hesitate to request for help and on the other hand, the experienced teachers don't offer assistance as most of them believe that the starting teachers should experience the induction period by their own and any help might interfere their learning during induction (Gordon & Maxey, 2000).

The induction period is crucial for teachers in which they often decide to stay in their job or leave it (Kessels, 2010). Schools recognise that starting teachers need additional support to overcome these challenges and therefore they offer various forms of induction programs. However, these inductions programmes still do not seem to be able to meet the needs of the starting teachers. In particular, the social aspects have not been properly

covered in induction programs while research shows that to be a major component of what a comprehensive induction program should offer.

Kessels (2010) indicates three main issues that should be addressed in inductions programs (Kessels, 2010): (a) socialization of starting teacher into the school (e.g. school rules, mission, curriculum), (b) further development of professional competences in terms of necessary knowledge and skills needed to be good teacher, and (c) personal development: support in learning to cope with stress, development of self confidence and improvement of teachers' well-being. Britton et al. (2003) and Kessels (2010) reveal the characteristics of a good induction program as follows. As they indicate, mentors should listen and respond to problems of starting teachers. They should keep an eye on the long-term learning goals of beginning teachers as learning to teach is a long-term activity. An induction program also should help starting teachers to feel like a member of "community of practice" through their relationships with peers. In this way, they can share their problems and concerns with peers and then, depending on the peers' experiences, they can receive solutions (Kessels, 2010). Moreover, if starting teachers have the possibility to observe good teaching practices, it helps them to have new insights and good examples for their own teaching process. If they also can be observed by others preferably by more experienced teachers, they can receive feedbacks that help new teachers to develop their skills (Kessels, 2010). In a good induction program, the starting teachers' concerns should be identified and then, suitable learning activities should be created to deal with identified concerns. Furthermore, an induction program should provide starting teachers with reflection (self-reflection or from others) in order to help them to develop their teaching identity (Kessels, 2010).

Although professional and personal development is also very important for starting teachers, research again points out that this needs to happen in a social context (Kelchtermans & Ballet, 2002; Schuck & Segal, 2002; Kessels, 2010). As mentioned, starting teachers hesitate to ask for help from their colleagues in their own schools. However, they are often eager to share their concerns and experiences with other new teachers and with their fellow students at the teacher education institutes (Schuck & Segal, 2002). Schuck and Segal (2002) pointed out that starting teachers prefer to receive support from outside of their own school and it would be beneficial for them if this kind of support offered from a network of starting teachers, experienced teachers and sometimes their supervising teachers at their teacher education institutes. In this way, the support comes from a network outside of their own school instead of following the traditional relationships between a new teacher and a mentor at the same school. As a result, an external social network is very helpful in addition to current induction programmes (Schuck, 2003). In this paper, we aim to explore the possibilities of such a social network in the form of Learning Networks.

Furthermore, starting teacher often would prefer to share their concerns with the peers they trust. On the other hand, they need to receive support from the most suitable people based on their certain problem. To address these issues, we can take advantage of recommender systems that help users to find the most suitable people or contents based on their past behaviour. Recommender systems have become popular mostly for their applications in e-commerce world such as Amazon (<http://www.amazon.com>) and ebay (<http://www.ebay.com>). However, they can be tailored to be applied in educational domain (Andronico et al., 2003; Tang & McCalla, 2005; Drachler, 2009). In this paper, we investigate whether recommenders systems approaches can be applied to assist the starting teachers in finding suitable people. In fact, we aim to propose a social recommender for alleviating problems of starting teachers and potentially as a supplementary tool to induction programs of schools.

The rest of the document is organized as follows: In Section 2, we explain why Learning Networks can supplement induction programmes, as they can support both professional and personal development and cater for the social aspects. In Section 3, we briefly describe the main aspects of recommender systems and how they are applied to educational systems. Then, we conduct an analysis of suitable educational recommender systems and draw further conclusions to Learning Networks for starting teachers. This information is required to explain our proposed solution that we will present in Section 4. Finally, we conclude and give an overview of the future steps in Section 5.

## Learning Networks

Starting teacher can take advantage by initiating and participating in an informal social network of colleagues like a professional learning community. In professional development of teachers, networked learning and

professional communities have been being increasingly accepted (Daly et al., 2009). A social network for beginning teachers can provide them with an infrastructure to share and exchange their knowledge. Next to those physical and local meetings within their school, an online social network can enhance their social support by enabling them to communicate with people who are far away and not in their direct physical environment. Such online social networks are also called Learning Networks (LN) that are nowadays more frequently used for professional development in various domains (Sloep & Kester, 2009). In an online Learning Network, beginning teachers can access learning materials and contents on a LN. They can share, annotate, rate and tags the contents and also exchange knowledge and experience with the other members of the LN.

Moreover, teachers profession relies on learning in their whole life during their education and training at the universities and also during their teaching as a teacher at schools. As LNs rely on social interaction between the members, they can provide teachers with social learning opportunities, which is a promising form of learning for lifelong learners. Sloep and Kester (2009) indicate that a social setting is beneficial for learners to improve their learning outcomes. Collaborating with others helps learners to feel less isolated as it provides them with a sense of belonging. Such a social setting and collaboration makes learners motivated to learn from each other and consequently, improves their learning outcomes (Sloep & Kester, 2009). Kester and Sloep (2009) introduce three main conditions that need to be met for social interactions to occur (Kester & Sloep, 2009): It should be possible for learners to meet again in the future (continuity), learners should be able to recognize and identify each other (recognizability), learners should be aware of the past behaviour of each other (history). Therefore, selecting the most suitable peers for a learner has been always challenging and highly important to address social interactions and social matching in LNs. The possibility of choices of the emerging contents and the people that are available in LNs is also known as information overload problem. To tackle this issue, we can take advantage of recommender systems which aim to provide users with the most suitable contents or people based on their past activities.

## Recommender systems

With the increasing amount of new information produced every day, there is a crucial need to design an efficient information retrieval system. Recommender Systems (RS) have become popular to address the information load problem. They personalize information for a user based her/his personal interests. They aim to assist users to find their desired information and to provide them with suitable contents based on their past behaviour. Recommender Systems have shown an acceptable performance in commercial domains such as movies, music or books (MovieLens, last.fm, Amazon). However, they are not particularly suitable to be applied in educational domain. Drachsler pointed out that educational RS should be able to recommend different learning activities to the learners even with the same interests but different proficiency level or prior-knowledge level, learning goal and context (Drachsler, 2009). For an educational RS, it's crucial to take into account the context of a learner. Most of the current approaches monitor the activities of successful learners to make recommendations on learning material regardless of the context of the learners (Andronico et al., 2003). Moreover, RS for learners should consider the changes of learning content over the time (Tang & McCalla, 2005). Tang and McCalla (2005) reported the differences between commercial recommenders and the RS for e-learning. They addressed the pedagogical features for making the recommendations in the context of recommending research papers to learners. There exist a number of approaches to generate recommendations for learners. We are going to review some of them in the following section but before that, we need to explain the main methods used in RS.

In general, there are two main methods used in RS: Content-based and Collaborative Filtering (CF). Content-based algorithms compute how relevant an item would be compared to items in which a target user has shown interests. In other words, content-based methods compare the representation of an item with a target user profile. Therefore, they develop a model of the user's preferences. However, the information for modelling the user interests often is not enough. (In fact, the user is needed to explicitly express the model of his/her preferences). Therefore, it imposes a high cognitive load on the user (Cantador, 2008). Collaborative Filtering (CF) is another technique for RS which purely depends on ratings of users instead of actual content description required by Content-based recommender systems. CF algorithms search for like-minded users that are introduced as neighbourhoods. CF methods predict an item's rating for a target user based on ratings of the user's neighbours. They provide a target user with top-N recommended neighbours and/or items. Hybrid recommenders take advantage of both content-based and collaborative filtering approaches to overcome their shortcomings. After giving this introduction to the RS methods, we are going to present examples of educational recommenders as they are related to the context of our social recommender for starting teachers.

## Educational applications of recommender systems

In this section, we give an overview of recommender systems that have been applied in an educational context. We will draw further conclusions from the review of these systems to propose our social recommender for the teacher Learning Network.

The Rule-Appling Collaborative Filtering (RACOFI) is an educational recommender system which integrates two techniques: a collaborative filtering engine based on users' ratings on learning resources and an inference rule engine using rules between the learning resources for making better recommendations (Anderson et al. 2003; Lemire et al. 2005). The rule engine assigns weight to the attributes and next, the user can control the weights. The rule engine mainly aims to make better recommendations by considering similarity between objects. Rafaeli et al. (2005) proposes QSIA (Questions Sharing and Interactive Assignments) in the context of online communities to share and recommend learning resources. In their approach, users are able to choose between having control on their recommended peers and using a collaborative filtering system. QSIA has been implemented for knowledge sharing among faculty and teaching assistants, high school teachers and among students (Manouselis et al., 2010). However, they have not yet published the evaluation results (Rafaeli et al., 2005). Tang and McCalla (2005) present a hybrid recommendation system to address pedagogical features when making recommendations regarding research papers. The system uses a model-based approach that first develops an individual model of learner by considering not only the learner interests and preferences but also pedagogical features of the learners like their background knowledge. However, this model-based recommender alone seems to be very costly. Therefore, they also take advantage of a classic CF algorithm to introduce the neighbors of a target learner by comparing both learner's interests and prior knowledge. CYCLADES

(<http://www.ercim.org/cyclades>), has been developed to provide users with digital archives which can be accessible through the open archives initiative (OAI) (<http://www.openarchives.org>). OAI has been introduced as an agreement among several digital archive providers to some minimal level of interoperability among them. In this system, every user is provided with her/his own information space like a folder containing metadata records, queries, ratings and annotations capable of managing and organizing by the user. In fact, CYCLADES is presented as a personalized and collaborative working environment in which users can search for their relevant information. The performance of CYCLADES has been evaluated in terms of accuracy of the generated recommendations by using several CF algorithms. The system has been evaluated by the system designers. Drachsler et al. (2009) propose a RS called ReMashed to address the learners in informal learning networks. ReMashed makes use of different Web2.0 sources for a user such as Flickr, Delicious.com, Sildeshare.com, Twitter and YouTube to identify the tags and ratings information of the respective user. The emerging tags and ratings data of users are mainly used to address new users. They generate recommendations by applying a classical collaborative filtering (Drachsler et al., 2009). Besides, they report users satisfaction with the system.

Beham et al. (2010) propose a people recommender called APOSDLE that is based on an ontology as a domain model. The ontology represents tasks, skills and topics in learning domain. This people RS is developed based on a user model which follows the aim of learning systems. APOSDLE infers knowledge and skills of users with respect to user interactions with the system (Beham et al., 2010). One of the main advantages of their people RS is that it does not depend on explicit feedbacks from users. Nevertheless, APOSDLE user model heavily depends on the user interactions and it might be challenging to generate recommendations for a new user who has no interactions with the system yet.

We summarise the main findings of the educational RS review in Table 1, where we point out the identified advantages and disadvantages of the discussed systems for our target group. The main conclusions of the review are presented in the next section.

**Table 1. State-of-the-art recommender systems in learning**

Approach	Advantages	Disadvantages	Recommended items
RACOFI (Anderson et al. 2003; Lemire et al. 2005)	Support rule-based approach to generate better recommendations	Needs explicit ratings No reported evaluation by users yet Sparsity and cold start problems	Music tracks
QSAI (Rafaeli et al. 2005)	Users can choose to have control on recommendation process	No published evaluation results yet Sparsity and cold start problems	Learning material: Assignments, exams, questions

CYCLADES (Avancini and Straccia 2005)	Providing recommendations over very large and distributed archives	Cold-start problem	Digital resources on OAI
Evolving e-learning system (Tang and McCalla, 2005)	Addressing cold-start problem No user model provided in the article	Using artificial learners Needs explicit feedbacks	Research papers
ReMashed (Drachsler et al. 2009)	Addressing cold-start problem Provides implicit ratings and tags from Web2.0 sources User evaluation is provided (user satisfaction)	Self-evaluation (in form of a questionnaire) of the user might be not very reliable Classic CF might face sparsity problem	Web pages, slides, PDF files, bookmarks, etc
APOSDLE (Beham et al., 2010)	Evolving user profiles User model does not depend on explicit data for the users	Model-based methods seems to be costly Cold-start problem	Knowledgeable people

### Aspects to consider

We present an overall view of the above mentioned educational recommenders in Table 1. In our work, it is not feasible to ask teachers to give explicit ratings to the recommended people or contents. As it is indicated in Table 1 ReMashed is the only approach that does not depend on explicit ratings given by a user. It instead takes advantage of implicit ratings and tags extracted from Web2.0 resources for a user to generate recommendations. However, ReMashed might face sparsity problem as it is based on a classical CF algorithm. Traditional CF based on similarity of users' ratings, suffers from sparsity problem when there is not a sufficient quantity of data available (e.g. due to lack of ratings) (Golbeck, 2005). In our case for teachers, we might face this problem as we are going to cluster them based on similarity of their profile and it is difficult to find similarity between teachers' profiles when we have no enough data from them yet. On the other hand, CF approaches can not make recommendations for a new user until she/he shows interests in an item (by rating or browsing the item) (Burke, 2002) which is referred to as cold-start problem. Evolving e-learning system (Tang & McCalla, 2005) uses artificial learners and human learners at the same time to overcome cold-start problem. To do so, Tang and McCalla (2005) generate artificial learners with different learner models and then, they assign papers to them randomly. They make "fake" ratings for the artificial learners based on their characteristics. When real learners start using the system, the "fake" ratings will be gradually replaced by the real ones. ReMashed (Drachsler et al. 2009) makes use of tags and ratings emerging from different Web2.0 sources for a user to address cold-start problem. We are going to adapt the approach used in ReMashed to tackle cold-start problem. APOSDLE finds the most suitable knowledgeable people for a learner based on the learner need. In our work, we follow the same goal as we aim to select the most suitable peers for a starting teacher. In APOSDLE (Beham et al., 2010), user profiles evolve by a learning mechanism based on users interactions with the system to provide more accurate recommendations. However, APOSDLE seems not to be able to generate recommendations for a new user who has no interactions with the system yet.

### Our proposed model

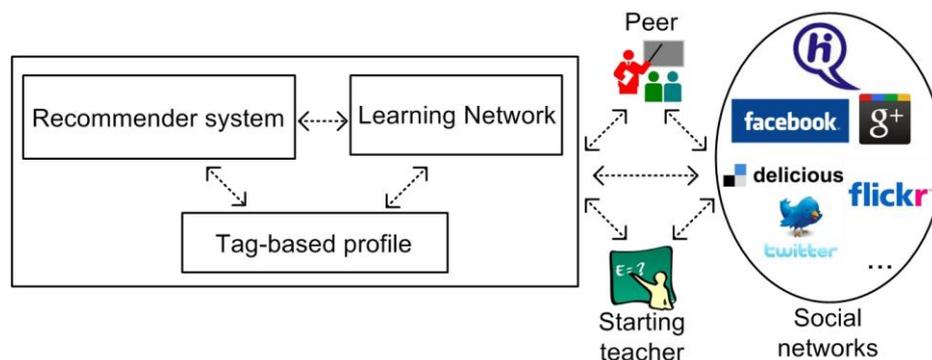
In this paper, we aim to propose a social recommender to find the most suitable peers for a starting teacher. As shown in Fig. 1, our presented model consists of three main modules. First, we need to provide teachers with an infrastructure that put them central as on online Learning Network in which they can share their concerns and solutions with others. Secondly, we need to develop user profile for our target users as it enables us to find the most suitable peers by matching the profiles. Therefore, we develop profile for a starting teacher based on her/his personal information, background knowledge, interests in terms of history of ratings, feedbacks and visited resources. We annotate the profile with tags that can be either provided explicitly by a starting teacher her/himself or extracted from the Web2.0 sources (i.e. delicious.com) similar to ReMashed (Drachsler et al. 2009). As such, the profiles gradually evolve as we receive more inputs from starting teachers in both ways.

The third module is a hybrid recommender system. We can take advantage of recommender systems to find either the most suitable people or to the most suitable contents for a certain information need of a beginning teacher. Content-based recommenders compare a user profile with representation of an item. We can also use them to find similarity between tag-based user profiles. In the starting phase of this project, we measure similarity between users based on the tags in their profile that mainly come from the collected data from questionnaire. If we measure similarity based on only tags emerging from the major problems beginning teachers face, the recommendations on people are those who faced a particular problem such as class management. However, we need to find the knowledgeable people who can provide good solutions to a problem for which a user needs assistance. So, we have to consider both background knowledge and maybe how many years the respective teacher has worked to be able to find more experienced teachers.

After the recommendation process, users are asked to give ratings to the recommended answers (or people). As content-based technique requires the user to express an explicit model of its preferences, the cognitive load on the user is high. Collaborative Filtering (CF) is the other technique for recommender systems that successfully overcomes these problems, since CF only depends on users' opinions and ratings of items instead of the explicit content description required by content-based recommenders. Therefore, to enhance the content-based system, we aim to use CF recommenders to find the most suitable peers for a particular teacher based on her/his information need. The classical CF approach is based on similarity between user profiles to cluster like-minded users. Then, CF algorithms can find the k-nearest neighbours for a target user to predict and recommend the items which might be in interest of the target user. We measure similarity between users based on the given ratings to the recommended people or items (only feasible after performing starting phase). Over the time, user profiles evolve and system learn how to generate better recommendations.

However, there are considerable issues that should be addressed carefully. These issues are explained as follows:

- Cold-start problem: For a starting teacher who has just joined our proposed system, we know only a little about her/his background knowledge or interests. Thus, we can adapt the approach presented by Drachler (2009) to overcome cold-start problem by using emerging tags and ratings data of starting teachers from Web2.0 sources. Furthermore, we aim to define and measure trust between starting teachers based on their common background knowledge and interests to address sparsity problem.
- Sparsity: As mentioned before, traditional CF based on similarity of users' ratings shows an acceptable performance only when there are sufficient data available (Golbeck, 2005). CF face sparsity problem when there are many starting teachers who have no common interests or background knowledge; this results in incomplete and inaccurate recommendations. Starting teachers often ask for assistance from whom they already know. On the other hand, their social interactions in a LN significantly improve if they feel that they are connected to trustful peers (other teachers, mentors, experts). So, we can take into account trust relationship between starting teachers. Although trust emerges from the similarity between profiles of starting teachers, it can be inferred to overcome sparsity problem. As a further step, we are going to measure mutual trust between starting teachers based on the common features of their profiles.



**Figure 1: the overall view of our proposed approach**

As a result, starting teachers will be the members of a LN where they can share, rate and tag resources. Moreover, the social recommender helps them to find the most suitable peers based on their activities in the LN.

## Conclusion and further work

In this paper, we explained Learning Networks as a supplementary solution to induction programs to provide starting teachers with both personal and professional development and also with social interactions. Then, we introduced recommender systems and their examples in educational domain. We described our proposed model for a Learning Network to assist teachers during their induction period as part of our ongoing research. Our proposed model consisted of three main modules: Learning Network as an infrastructure that presents an online social network for teachers, tag-based profile is a module for either creating or updating user profile based on the data from questionnaire and the user activities within the system, and finally, recommender system enable us to find the most suitable peers for a starting teacher. Of course, the final objective is to verify our research question and proposed model. However, the next future step of the project will be to further investigate the induction problems and confirm them in the Dutch educational system. We will use in-depth interviews and questionnaires to identify what the main problems are, and what the preferred solution would be. Next to that, we will also investigate the digital literacy of the young teachers regarding social networks and the use of social media as that is a crucial part of the project. The outcome of interviews and questionnaires will be used to decide which of the induction problems are suitable for our solution, to customize our model and to assist in designing the learning network.

## References

- Anderson M., Ball M., Boley H., Greene S., Howse N., Lemire D., McGrath S. (2003). "RACOFI: A Rule-Applying Collaborative Filtering System", Paper presented at the conference IEEE/WIC COLA'03, October 2003, Halifax, Canada.
- Beham, G., Kump, B., Ley, T., Lindstaedt, S. Recommending knowledgeable people in a work-integrated learning system. Proceedings of the 1st Workshop on Recommender Systems for Technology Enhanced Learning (RecSysTEL 2010), Volume 1, Issue 2, 2010, Pages 2783-2792
- Burke, R. Hybrid Web Recommender Systems. In Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.). The Adaptive Web: Methods and Strategies of Web Personalization., Lecture Notes in Computer Science, Vol. 4321, pp. 377-408, Springer, Berlin-Heidelberg, 2007.
- Daly, A. J., Moolenaar, N. M., Bolivar, J. M., & Burke, P. (2010). Relationships in reform: the role of teachers' social networks. *Journal of Educational Administration*, 48(3), 359-391. doi: 10.1108/09578231011041062
- Drachler, H., Pecceu, D., Arts, T., Hutten, E., Rutledge, L., Van Rosmalen, P., Hummel, H.G.K., Koper, R.: ReMashed - Recommendations for Mash-Up Personal Learning Environments. In: Cress, U., Dimitrova, V., Specht, M. (eds.): *Learning in the Synergy of Multiple Disciplines*, EC-TEL 2009, LNCS 5794, Berlin; Heidelberg; New York: Springer, pp788-793, 2009a
- Golbeck, J., "Trust and nuanced profile similarity in online social networks," MINDSWAP Technical Report TR-MS1284, University of Maryland, College Park, Tech. Rep., 2007. [Online]. Available: <http://trust.mindswap.org/papers/trustStudy.pdf>
- Gordon, S.P. & Maxey, S. (2000) *How to Help Beginning Teachers Succeed*, 2nd edn. Alexandria: Association for Supervision and Curriculum Development.
- Kelchtermans, G., & Ballet, K. (2002). The micropolitics of teacher induction. A narrativebiographical study on teacher socialisation. *Teaching and Teacher Education*, 18, 105-120.
- Kessels, C. (2010). The influence of induction programs on beginning teachers' well-being and professional development. Unpublished Dissertation, University of Leiden, Leiden.
- Kester, L., & Sloep, P. B. (2009). Knowledge dating and knowledge sharing in ad-hoc transient communities. In R. Koper (Ed.), *Learning Network Services for Professional Development* (pp. 43-56). Berlin, Germany: Springer Verlag.
- Lemire, D., Boley, H., McGrath, S., & Ball, M. (2005). Collaborative Filtering and Inference Rules for Context-Aware Learning Object Recommendation. *International Journal of Interactive Technology and Smart Education*, 2(3).
- Rafaeli, S., Dan-Gur, Y., & Barak, M. (2005). Social Recommender Systems: Recommendations in Support of E-Learning. *International Journal of Distance Education Technologies*, 3(2), 29-45.
- Schuck S., Getting help from the outside: developing a support network for beginning teachers, *The Journal of Educational Enquiry*, Vol 4, No 1 (2003)
- Sloep, P., & Kester, L. (2009). From Lurker to Active Participant. In R. Koper (Ed.), *Learning Network Services for Professional Development* (pp. 17-25). Berlin, Germany: Springer Verlag.
- Tang T.Y., McCalla G.I., "Smart Recommendation for an Evolving E-Learning System: Architecture and Experiment", *International Journal on E-Learning*, 4 (1), 105-129, 2005.