Chapter 12
Recommender Systems in Technology Enhanced Learning

Nikos Manouselis, Hendrik Drachsler, Riina Vuorikari, Hans Hummel and Rob Koper

Abstract Technology enhanced learning (TEL) aims to design, develop and test socio-technical innovations that will support and enhance learning practices of both individuals and organisations. It is therefore an application domain that generally covers technologies that support all forms of teaching and learning activities. Since information retrieval (in terms of searching for relevant learning resources to support teachers or learners) is a pivotal activity in TEL, the deployment of recommender systems has attracted increased interest. This chapter attempts to provide an introduction to recommender systems for TEL settings, as well as to highlight their particularities compared to recommender systems for other application domains.

Nikos Manouselis
Greek Research and Technology Network (GRNET S.A.), 56 Messogeion Av., 115 27, Athens, Greece e-mail: `nikosm@ieee.org`

Hendrik Drachsler
Centre for Learning Sciences and Technologies (CELSTEC), Open Universiteit Nederland e-mail: `hendrik.drachsler@ou.nl`

Riina Vuorikari,
European Schoolnet (EUN), 24, Rue Paul Emile Janson, 1050 Brussels, Belgium e-mail: `riina.vuorikari@eun.org`

Hans Hummel
Centre for Learning Sciences and Technologies (CELSTEC), Open Universiteit Nederland e-mail: `hans.hummel@ou.nl`

Rob Koper
Centre for Learning Sciences and Technologies (CELSTEC), Open Universiteit Nederland e-mail: `rob.koper@ou.nl`

F. Ricci et al. (eds.), *Recommender Systems Handbook*,
DOI 10.1007/978-0-387-85820-3_12,

12.1 Introduction

Technology enhanced learning (TEL) aims to design, develop and test socio-technical innovations that will support and enhance learning practices of both individuals and organisations. It is therefore an application domain that generally covers technologies that support all forms of teaching and learning activities. Since information retrieval (in terms of searching for relevant learning resources to support teachers or learners) is a pivotal activity in TEL, the deployment of recommender systems has attracted increased interest.

As in any other field where there is a massive increase in product variety, in TEL there is also a need for better findability of (mainly digital) learning resources. For instance, during the past few years, numerous repositories with digital learning resources have been set up [96]. Prominent US examples are repositories such as MERLOT (http:// www.merlot.org) that has more than 20,000 learning resources (and about 70,000 registered users), and OER Commons (www.oercommons.org) with about 18,000 resources. In Europe, a typical example is European Schoolnet's Learning Resource Exchange (http://lreforschools.eun.org) that federates more than 43,000 learning resources from 25 different content providers in Europe and beyond. Apart from learning content, learning resources may also include learning paths (that can help them navigate through appropriate learning resources) or relevant peer-learners (with whom collaborative learning activities can take place).

In this plethora of online learning resources available, and considering the various opportunities for interacting with such resources that often occur in both formal and non-formal settings, all user groups of TEL systems can benefit from services that help them identify suitable learning resources from a potentially overwhelming variety of choices. As a consequence, the concept of recommender systems has already appeared in TEL. Latest efforts to identify relevant research in this field, and to bring together researchers working on similar topics, have been the annual workshop series of Social Information Retrieval for Technology Enhanced Learning (SIRTEL), and a Special Issue on Social Information Retrieval for TEL in the Journal of Digital Information [31]. These efforts resulted in a number of interesting conclusions, the main ones being that:

1. There is a large number of recommender systems that have been deployed (or that are currently under deployment) in TEL settings;
2. The information retrieval goals that TEL recommenders try to achieve are often different to the ones identified in other systems (e.g. product recommenders);
3. There is a need to identify the particularities of TEL recommender systems, in order to elaborate on methods for their systematic design, development and evaluation.

In this direction, the present chapter attempts to provide an introduction to issues related to the deployment of recommender systems in TEL settings, keeping in mind the particularities of this application domain. The main contributions of this chapter are the following:

- Discuss the background of recommender systems in TEL, especially in relation to the particularities of the TEL context.
- Reflect on user tasks that are supported in TEL settings, and how they compare to typical user tasks in other recommender systems.
- Review related work coming from adaptive educational hypermedia (AEH) systems and the learning networks (LN) concept.
- Assess the current status of development of TEL recommender systems.
- Provide an outline of particularities and requirements related to the evaluation of TEL recommender systems that can provide a basis for their further application and research in educational applications.

12.2 Background

TEL as context

TEL relates to data generated in different types of educational settings, which are usually called macro-context [99]. This concept has significant influence on which user actions are possible and how they can be interpreted. Examples of these dimensions of macro-context include dimensions such as educational level, formal and informal learning, delivery setting and different user roles. Examples of the educational level are K-12 education, Higher Education (HE), Vocational Education and Training (VET) and workplace training.

A formal setting for learning includes learning offers from educational institutions (e.g. universities, schools) within a curriculum or syllabus framework, and is characterised as highly structured, leading to a specific accreditation and involving domain experts to guarantee quality. This traditionally occurs in teacher-directed environments with person-to-person interactions, in a live and synchronous manner.

An informal setting, on the other hand, is described in the literature as a learning phase of so called lifelong learners who are not participating in any formal learning and are responsible for their own learning pace and path [17, 64]. The learning process depends to a large extent on individual preferences or choices and is often self-directed [8]. The resources for informal learning might come from sources such as expert communities, work context, training or even friends might offer an opportunity for an informal competence development.

The TEL involvement can be characterised by the provision of blended learning opportunities to purely distant educational ones [71]. Blended learning combines traditional face-to-face learning with computer-supported learning [36]. Distance education, on the other hand, can be delivered using TEL environments in either synchronous or asynchronous ways. Traditionally, distance learning was more related to self-paced learning and learning-materials interactions that typically occurred in an asynchronous way [36]. However, live streaming and virtual, personal learning

Table 12.1: User tasks supported by current recommender systems and requirements for TEL recommender systems

Tasks	*Description*	*Generic recommender*	*TEL recommenders*	*New requirements*
		Existing User Tasks supported by Recommender Systems		
1. ANNOTATION IN CONTEXT	Recommendations while user carries out other tasks	E.g. predicting how relevant the links are within a web page	E.g. predicting relevance/usefulness of items in the reading list of a course	Explore attributes for representing relevance/usefulness in a learning context
2. FIND GOOD ITEMS	Recommendations of suggested items	E.g. receiving list of web pages to visit	E.g. receiving a selected list of online educational resources around a topic	None
3. FIND ALL GOOD ITEMS	Recommendation of all relevant items	E.g. receiving a complete list of references on a topic	E.g. suggesting a complete list of scientific literature or blog postings around a topic	None
4. RECOMMEND SEQUENCE	Recommendation of a sequence of items	E.g. receive a proposed sequence of songs	E.g. receiving a proposed sequence through resources to achieve a particular learning goal	Explore formal and informal attributes for representing relevancy to a particular learning goal
5. JUST BROWSING	Recommendations out of the box while user is browsing	E.g. people that bought this, have also bought that	E.g. receiving recommendations for new courses on the university site	Explore formal and informal attributes for representing relevance/usefulness in a learning context
6. FIND CREDIBLE RECOMMENDER	Recommendations during initial exploration/testing phase of a system	E.g. movies that you will definitely like	E.g. restricting course recommendations to ones with high confidence /credibility	Explore criteria for measuring confidence and credibility in formal and informal learning
		TEL User Tasks that could be supported by Recommender Systems		
1. FIND NOVEL RESOURCES	Recommendations of particularly new or novel items	E.g. receiving recommendations about latest additions or particularly controversial items	E.g. receiving very new and/or controversial resources on covered topics	Explore recommendation techniques that select items beyond their similarity
2. FIND PEERS	Recommendation of other people with relevant interests	E.g. being suggested profiles of users with similar interests	E.g. being suggested peer students in the same class	Explore attributes for measuring the similarity with other people
3. FIND GOOD PATHWAYS	Recommendation of alternative learning paths through learning resources	E.g. receive alternative sequences of similar songs	E.g. receiving a list of alternative learning paths over the same resources to achieve a specific learning goal	Explore criteria for the construction and suggestion of alternative (but similar) sequences

environments (e.g. Web 2.0) have facilitated the development of synchronous distance learning services in formal educational settings.

Lastly, different actors and needs can be identified in TEL. A distinction can be made between the teacher-directed interaction and learner-directed learning processes. This has ramifications concerning the intended users of TEL environments. While macro-context has large implications for interpretation and design, its aspects are fairly agreed upon, and it is comparatively easy to measure. Micro-context is a more contested notion and more difficult to measure. However, while macro-context is domain-specific, concepts for micro-context range over more diverse fields.

TEL Recommendation goals

In the past, the development of recommender systems has been related to a number of relevant user tasks that the recommender system supports within some particular application context (see Chapter 7). More specifically, Herlocker et al. [38] have related popular (or less popular) user tasks with a number of specific recommendation goals that are included in Table 1. Generally speaking, most of these already identified recommendation goals and user tasks are valid in the case of TEL recommender systems as well. For example, in a recommender system supporting learners to achieve a specific learning goal, "providing annotation in context" or "recommending a sequence" of learning resources are relevant tasks. In Table 1, examples are given of how recommendation could support TEL-relevant activities for all the tasks that Herlocker et al. [38] have identified. In addition, it includes a comment about any additional requirements that this brings forward for the developers of TEL recommender systems.

On the other hand, in comparison to the typical item recommendation scenario, there are several particularities to be considered regarding what kind of learning is desired, e.g. learning a new concept or reinforce existing knowledge may require different type of learning resources. This is reflected in the second part of Table 1, with examples of user tasks that are particularly interesting for TEL. Again, a comment on any additional requirements for developers of TEL recommenders is included.

Apart from this initial identification of tasks, recommendation in a TEL context has many particularities that are based on the richness of the pedagogical theories and models. For instance, for learners with no prior knowledge in a specific domain, relevant pedagogical rules such as Vygotsky's "zone of proximal development" could be applied: e.g. 'recommended learning objects should have a level slightly above learners' current competence level' [102]. Different from buying products, learning is an effort that often takes more time and interactions compared to a commercial transaction. Learners rarely achieve a final end state after a fixed time. Instead of buying a product and then owning it, learners achieve different levels of competences that have various levels in different domains. In such scenarios, it is important to identify the relevant learning goals and support learners in achieving them. On the other hand, depending on the context, some particular user task may be prioritised. This could call for recommendations whose time span is longer than the one of product recommendations, or recommendations of similar learning resources, since recapitulation and reiteration are central tasks of the learning process [68].

As for teacher-centered learning context, different tasks need to be supported. These tasks cover both the ones related to the preparation of lessons, the delivery of a lesson (i.e. the actual teaching), and the ones related to the evaluation/assessment. For instance, to prepare a lesson the teacher has certain educational goals to fulfil and needs to match the delivery methods to the profile of the learners (e.g. their previous knowledge). Lesson preparation can include a variety of information seeking tasks, such as finding content to motivate the learners, to recall existing knowledge, to illustrate, visualise and represent new concepts and information. The delivery can be supported in using different pedagogical methods (either supported with TEL or not), whose effectiveness is evaluated according to the goals set. A TEL recommender system could support one or more of these tasks, leading to a variety of recommendation goals.

Thus, although the previously identified user tasks and recommendation goals can be considered valid in a TEL context, there are several particularities and complexities. This means that simply transferring a recommender system from an existing (e.g. commercial) content to TEL may not accurately meet the needs of the targeted users. In TEL, careful analysis of the targeted users and their supported tasks should be carried out, before a recommendation goal is defined and a recommender system is deployed. This means that the TEL recommendation goals can be rather complex: for example, a typical TEL recommender system could suggest a number of alternative learning paths throughout a variety of learning resources, either in the form of learning sequences or hierarchies of interacting learning resources. This should take place in a pedagogically meaningful way that will reflect the individual learning goals and targeted competence levels of the user, depending on proficiency levels, specific interests and the intended application context. A number of context variables have to be considered, such as user attributes, domain characteristics, and intelligent methods that can be engaged to provide personalised recommendations. Extensive work on these topics has been carried out in the past, in the area of adaptive educational hypermedia systems.

12.3 Related Work

Web systems generally suffer from the inability to satisfy the heterogeneous needs of many users. To address this challenge, a particular strand of research that has been called *adaptive web systems* (or *adaptive hypermedia*) tried to overcome the shortcomings of traditional ‘one-size-fits-all’ approaches by exploring ways in which Web-based could adapt their behaviour to the goals, tasks, interests, and other characteristics of interested users [12]. A particular category of adaptive systems has been the one dealing with educational applications, called *adaptive educational hy-*

permedia (AEH) systems. Since one can say that AEH systems address issues of high relevance to TEL recommender systems, this section provides a brief overview of related work, trying to identify commonalities and differences that could be of relevance for TEL recommenders.

Adaptive Educational Hypermedia

Adaptive web systems belong to the class of user-adaptive software systems [87]. According to Oppermann [73] a system is called adaptive “if it is able to change its own characteristics automatically according to the user’s needs”. Adaptive systems consider the way the user interacts with the system and modify the interface presentation or the system behaviour accordingly [108]. Jameson [43] adds an important characteristic: “A user-adaptive system is an interactive system which adapts its behaviour to each individual user on the basis of nontrivial inferences from information about that user”.

Adaptive systems help users find relevant items in a usually large information space, by essentially engaging three main adaptation technologies [12]: adaptive content selection, adaptive navigation support, and adaptive presentation. The first of these three technologies comes from the field of adaptive information retrieval (IR) [6] and is associated with a search-based access to information. When the user searches for relevant information, the system can adaptively select and prioritise the

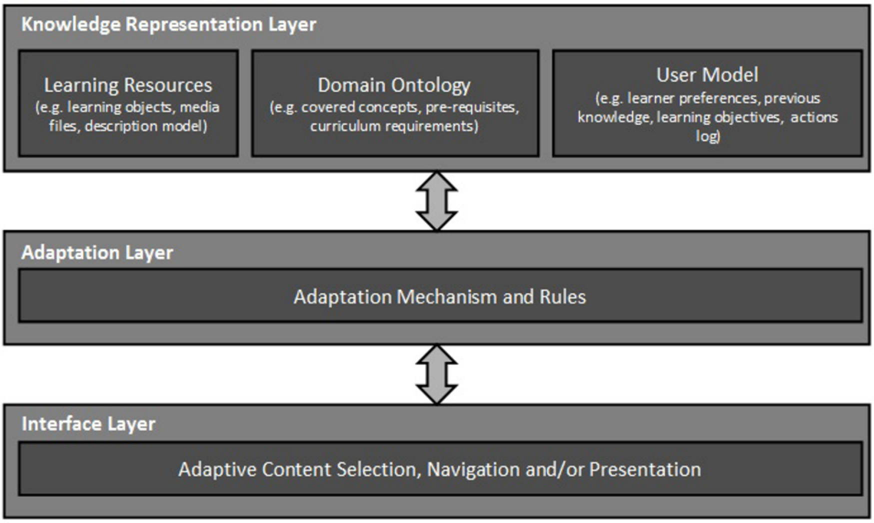


Fig. 12.1: Generic layers within a simplified example architecture of an educational AEH (adapted from [47]

most relevant items. The second technology was introduced by adaptive hypermedia systems [9] and is associated with a browsing-based access to information. When the user navigates from one item to another, the system can manipulate the links (e.g., hide, sort, annotate) to guide the user adaptively to most relevant information items. The third technology has its roots in the research on adaptive explanation and adaptive presentation in intelligent systems [70, 76]. It deals with presentation, not access to information. When the user gets to a particular page, the system can present its content adaptively.

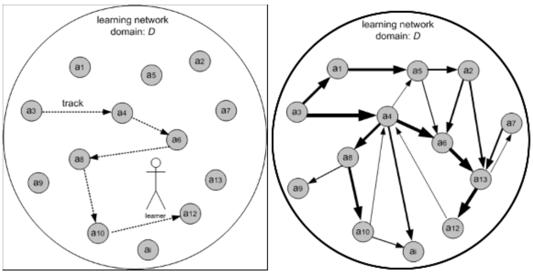
As Brusilovksy [10] describes, educational hypermedia was one of the first application areas of adaptive systems. A simplified architecture of the layers within an educational AEH system is presented in Figure 12.1. This architecture includes: a layer including the representation and organisation of knowledge about educational content (*learning resources*), the domain (*domain ontology*), and the user (*user model*); a layer that includes the adaptation mechanisms and rules; and a layer that provides the run-time adaptation results to the user. A number of pioneer adaptive educational hypermedia systems were developed between 1990 and 1996, which he roughly divided into two research streams. The systems of one of these streams were created by researchers in the area of intelligent tutoring systems (ITS) who were trying to extend traditional student modelling and adaptation approaches developed in this field to ITS with hypermedia components [14, 34, 77]. The systems of the other stream were developed by researchers working on educational hypermedia in an attempt to make their systems adapt to individual students [19, 21, 39, 48]. AEH research has often followed a top-down approach, greatly depending on expert knowledge and involvement in order to identify and model TEL context variables. For example, Cristea [18] describes a number of expertise-demanding tasks when AEH content is authored: initially creating the resources, labelling them, combining them into what is known as a domain model; then, constructing and maintaining the user model in a static or dynamic way, since it is crucial for achieving successful adaptation in AEH. Generally speaking, in AEH a large amount of user-related information (characterising needs and desires) has to be encoded in the content creation phase. This can take place in formal educational settings when the context variables are usually known, and there is a large amount of AEH research (e.g. dealing with learner and domain models) that can be considered and reused within TEL recommender research. On the other hand, in non-formal settings less expert-demanding approaches need to be explored.

Learning Networks

Another strand of work includes research where the context variables are extracted from the contributions of the users. A category of such systems includes *learning networks*, which connect distributed learners and providers in certain domains [53, 54]. The design and development of learning networks is highly flexible, learner-centric and evolving from the bottom upwards, going beyond formal course and programme-centric models that are imposed from the top downwards. A learning network is populated with many learners and learning activities provided by different stakeholders. Each user is allowed to add, edit, delete or evaluate learning resources at any time.

The concept of learning networks [54] provides methods and technical infrastructures for distributed lifelong learners to support their personal competence development. It takes advantages of the possibilities of the Web 2.0 developments and describes the new dynamics of learning in the networked knowledge society. A learning network is learner-centered and its development emerges from the bottom-up through the participation of the learners. Emergence is the central idea of the learning network concept. Emergence appears when an interacting system of individual actors and resources self-organises to shape higher-level patterns of behaviour [35, 45, 103].

We can imagine users (e.g. learners) interacting with learning activities in a learning network while their progress is being recorded. Indirect measures like time or learning outcomes, and direct measures like ratings and tags given by users allow identify paths in a learning network which are faster to complete or more attractive than others (e.g. [28, 100]). This information can be fed back to other learners in the learning network, providing collective knowledge of the 'swarm of learners' in the learning network. Most learning environments are designed only top-down as often times their structure, learning activities and learning routes are predefined by an educational institution. Learning networks, on the other hand, take advantage of the user-generated content that is created, shared, rated and adjusted by using Web 2.0 technologies. In the field of TEL, several European projects address these bottom-up approaches of creating and sharing knowledge. A large EU initiative that addresses the creation of informal learning networks is the TENcompetence project [110].



(a) (b)

Fig. 12.2: Evolution of a learning network (left: starting phase with a first learner moving through possible learning activities; right: advanced phase showing emerging learning paths from the collective behavior of all learners)

Another category of systems that formulate and define their context variables following a bottom-up approach, are Mash-Up Personal Learning Environments

(MUPPLE) [109]. First such approaches were created in [62, 63, 109]. The iCamp EU-initiative explicitly addresses the integration of Web2.0 sources into MUPPLE, by creating a flexible environment that allows learners to create their own environments for certain learning activities. MUPPLEs are a kind of instance of the learning network concept and therefore share several characteristics with it. They also support informal learning as they require no institutional background and focus on the learner instead of institutional needs like student management or assessments. The learners do not participate in formal courses and neither receive any certification for their competence development. A common problem for MUPPLEs is the amount of data that is gathered already in a short time frame and the unstructured way it is collected. This can make the process of user and domain modelling demanding and unstructured. On the other hand, this is often the case in recommender systems as well, when user and item interactions are explored, e.g. in order to identify user and item similarities.

Similarities and differences

Many of the AEH systems address formal learning (e.g. [3, 20, 57]), have equally fine granulated knowledge domains and can therefore offer personalised recommendations to the learners. They take advantage of technologies like metadata and ontologies to define the relationships, conditions, and dependencies of learning resources and learner models. These systems are mainly used in 'closed-corpus' applications [16] where the learning resources can be described by an educational designer through semantic relationships and is therefore a formal learning offer. As mentioned before, in formal educational settings (such as universities) there are usually well- structured formal relationships like predefined learning plans (curriculum) with locations, student/teacher profiles, and accreditation procedures. All this metadata can be used to recommend courses or personalise learning through the adaptation of the learning resources or the learning environment to the students [5]. One interesting direction in this research is the work on adaptive sequencing which takes into account individual characteristics and preferences for sequencing learning resources [47]. In AEH there are many design activities needed before the runtime and also during the maintenance of the learning environment. In addition, the knowledge domains in the learning environment need to be described in detail. These aspects make adaptive sequencing and other adaptive hypermedia techniques rather demanding in TEL recommendation.

Informal learning networks emerge without some highly structured domain model representation. Mining techniques need to be used in order to create some representation of the user or domain model. For instance, prior knowledge in informal learning is a rather diffuse parameter because it relies on information given by the learners without any standardisation. To handle the dynamic and diffuse characteristic of prior knowledge, and to bridge the absence of a knowledge domain model, probabilistic techniques like latent semantic analysis are promising [97]. The absence of maintenance and structure in informal learning is also called the 'open corpus problem'. The open corpus problem applies when an unlimited set of documents is given that cannot be manually structured and indexed with domain concepts and metadata from a community [16] and applies to informal learning networks. Therefore, bottom-up recommendation techniques like collaborative filtering are more appropriate because they require nearly no maintenance and improve through the emergent behaviour of the community. Drachsler et al. [25] analysed how various types of collaborative filtering techniques can be used to support learners in informal learning networks. Following their conclusions we have to consider the different environmental conditions of informal learning, such as the lack of maintenance and less formal structured learning objects, in order to provide an appropriated navigation support to recommender systems. Learning networks are mainly structured based on user-generated information and interactions.

Besides the already mentioned differences for prior knowledge in informal learning, there are also differences in the data sets which are derived from environmental conditions. Normally, the numbers of ratings obtained in recommender systems is usually very small compared to the number of ratings that have to be predicted. Effective prediction by ratings based on small amounts is very essential for recommender systems and has an effect on the selection of a specific recommendation technique. Formal learning can rely on regular evaluations of experts or students upon multiple criteria (e.g., pedagogical quality, technical quality, ease of use) [67], but in informal learning environments such evaluation procedures are unstructured and few. Formal learning environments like universities often have integrated evaluation procedures for a regular quality evaluation to report to their funding body. With these integrated evaluation procedures more dense data sets can be expected. As a conclusion, the data sets in informal learning context are characterised by the "Sparsity problem" caused by sparse ratings in the data set. Multi-criteria ratings (see Chapter 24) could be beneficial for informal learning to overcome the "Sparsity problem" of the data sets. These multi-criteria ratings have to be reasonable for the community of lifelong learners. The community could rate learning resources on various levels, such as required prior knowledge level (novice to expert), the presentation style of learning resources, and even the level of attractiveness, because keeping students satisfied and motivated is a vital criteria in informal learning. These explicit rating procedures should be supported with several indirect measures like 'Amount of learners using the learning resource, 'Amount of adjustments of a learning resources", in order to measure how up-to-date the learning resource is.

Informal learning is therefore different from well-structured domains like formal learning. Recommender systems for informal learning could have no official maintenance by an institution, mostly rely on its community, and not contain well-defined metadata structures. Moreover, where formal learning is characteristically top-down designed and develop learning offers (closed-corpus), informal learning offers are emerging from the bottom-up through the communities (open-corpus). Therefore, it will be difficult to transfer and apply recommender systems even from formal to non-formal settings (and vice-versa), since user tasks and recommendation goals are often substantially different.

Table 12.2: Recommendation techniques and their usefulness for TEL by Drachsler et al. [24]

Name	*Short description*	*Advantages*	*Disadvantages*	*Usefulness for TEL*
		Collaborative filtering (CF) techniques		
1. User-based CF	Users that rated the same item similarly probably have the same taste. Based on this assumption, this technique recommends unseen items already rated by similar users.	- No content analysis - Domain-independent - Quality improves over time - Bottom-up approach - Serendipity	- New user problem - New item problem - Popular taste - Scalability - Sparsity - Cold-start problem	- Benefits from experience - Allocates learners to groups (based on similar ratings)
2. Item-based CF	Focus on items, assuming that items rated similarly are probably similar. It recommends items with highest correlation (based on ratings to the items).	- No content analysis - Domain-independent - Quality improves over time - Bottom-up approach - Serendipity	- New item problem - Popular taste - Sparsity - Cold-start problem	- Benefits from experience
3. Stereotypes or demographics CF	Users with similar attributes are matched, then recommends items that are preferred by similar users (based on user data instead of ratings).	- No cold-start problem - Domain-independent - Serendipity	- Obtaining information - Insufficient information - Only popular taste - Obtaining metadata information - Maintenance ontology	- Allocates learners to groups - Benefits from experience - Recommendation from the beginning of the RS
		Content-based (CB) techniques		
4. Case-based reasoning	Assumes that if a user likes a certain item, s/he will probably also like similar items. Recommends new but similar items.	- No content analysis - Domain-independent - Quality improves over time	- New user problem - Overspecialisation - Sparsity - Cold-start problem	- Keeps learner informed about learning goal - Useful for hybrid RS
5. Attribute-based techniques	Recommends items based on the matching of their attributes to the user profile. Attributes could be weighted for their importance to the user.	- No cold-start problem - No new user / new item problem - Sensitive to changes of preferences - Can include non-item related features - Can map from user needs to items	- Does not learn - Only works with categories - Ontology modeling and maintenance is required - Overspecialisation	- Useful for hybrid RS - Recommendation from the beginning

A critical assessment of recommender techniques regarding their applicability and usefulness in TEL has taken place by Drachsler et al. [24], and is briefly presented in Table 2. This Table provides an initial overview of advantages and disadvantages of each technique, and reports the envisaged usefulness of each technique for TEL recommenders. Nevertheless, it aims to serve as an initial basis for such a discussion, since a more detailed and elaborate survey of all existing recommendation methods and techniques can take place in the future.

12.4 Survey of TEL Recommender Systems

In the TEL domain a number of recommender systems have been introduced in order to propose learning resources to users. Such systems could potentially play an important educational role, considering the variety of learning resources that are published online and the benefits of collaboration between tutors and learners [81, 82, 59]. The following paragraphs review some recent approaches and provide an assessment of their status of development and evaluation.

One of the first attempts to develop a collaborative filtering system for learning resources has been the Altered Vista system [81, 82, 83]. The aim of this study was to explore how to collect user-provided evaluations of learning resources, and then to propagate them in the form of word-of-mouth recommendations about the qualities of the resources. The team working on Altered Vista explored several relevant issues, such as the design of its interface [82], the development of non-authoritative metadata to store user-provided evaluations [81], the design of the system and the review scheme it uses [83], as well as results from pilot and empirical studies from using the system to recommend to the members of a community both interesting resources and people with similar tastes and beliefs [83, 104].

Another system that has been proposed for the recommendation of learning resources is the RACOFI (Rule-Applying Collaborative Filtering) Composer system [2, 60, 61]. RACOFI combines two recommendation approaches by integrating a collaborative filtering engine, that works with ratings that users provide for learning resources, with an inference rule engine that is mining association rules between the learning resources and using them for recommendation. RACOFI studies have not yet assessed the pedagogical value of the recommender, nor do they report some evaluation of the system by users. The RACOFI technology is supporting the commercial site inDiscover (http://www.indiscover.net) for music tracks recommendation. In addition, other researchers have reported adopting RACOFI's approach in their own systems as well [32].

The QSIA (Questions Sharing and Interactive Assignments) for learning resources sharing, assessing and recommendation has been developed by Rafaeli et al. [78, 79]. This system is used in the context of online communities, in order to harness the social perspective in learning and to promote collaboration, online recommendation, and further formation of learner communities. Instead of developing a typical automated recommender system, Rafaeli et al. chose to base QSIA

Table 12.3: Implemented TEL recommender systems reported in literature

System	Status	Evaluator focus	Evaluation roles
Altered Vista [80, 81, 82, 105]	Full system	Interface, Algorithm, System usage	Human users
RACOFI [2, 61]	Prototype	Algorithm	System designers
QSAI [78, 79]	Full system	—	—
CYCLADES [4]	Full system	Algorithm	System designers
CoFind [29, 30]	Prototype	System usage	Human users
Learning object sequencing [88]	Prototype	System usage	Human users
Evolving e-learning system [90, 91, 92, 93]	Full system	Algorithm, System usage	Simulated users, Human users
ISIS - Hybrid Personalised Recommender System [28]	Prototype	Algorithm, System usage	Human users
Multi-Attribute Recommendation Service [67]	Prototype	Algorithm	System designers
Learning Object Recommendation Model [95]	Design	—	—
RecoSearch [32]	Design	—	—
Simulation environment [72]	Full system	Algorithm	Simulated users
ReMashed [26, 27]	Full system	Algorithm, System usage	Human users
CourseRank [55, 56]	Full system	System usage	Human users
CBR Recommender Interface [33]	Prototype	—	—
APOSDLE Recommendation Service [1]	Prototype	—	—
A2M Recommending System [86]	Prototype	—	—
Moodle Recommender System [44]	Prototype	Algorithm, System usage	Human users
LRLS [41]	Prototype	System usage, Learner performance	Human users
RPL recommender [49]	Prototype	System usage	System designers, Human users

on a mostly user-controlled recommendation process. That is, the user can decide whether to assume control on who advises (friends) or to use a collaborative filtering service. The system has been implemented and used in the context of several learning situations, such as knowledge sharing among faculty and teaching assistants, high school teachers and among students, but no evaluation results have been reported so far [78, 79].

In this strand of systems for collaborative filtering of learning resources, the CYCLADES system [4] has proposed an environment where users search, access, and evaluate (rate) digital resources available in repositories found through the Open Archives Initiative (OAI, http://www.openarchives.org). Informally, OAI is an agreement between several digital archives providers in order to offer some minimum level of interoperability between them. Thus, such a system can offer recommendations over resources that are stored in different archives and accessed through an open scheme. The recommendations offered by CYCLADES have been evaluated through a pilot study with about 60 users, which focused on testing the performance (predictive accuracy) of several collaborative filtering algorithms.

A related system is the CoFind prototype [29, 30]. It also used digital resources that are freely available on the Web but it followed a new approach by applying for the first time folksonomies (tags) for recommendations. The CoFind developers stated that predictions according to preferences were inadequate in a learning context and therefore more user driven bottom-up categories like folksonomies are important.

A typical, neighborhood-based set of collaborative filtering algorithms have been tried in order to support learning object recommendation by Manouselis et al. [67]. The innovative aspect of this study is that the engaged algorithms have been multi-attribute ones, allowing the recommendation service to consider multi-dimensional ratings that users provide on learning resources. An interesting outcome from this study in comparison to initial experiments using the same algorithms (e.g. [65]), is that it seems that the performance of the same algorithms is changing, depending on the context where testing takes place. For instance, the results from the comparative study of the same algorithms in an e-commerce [65] and a TEL setting [67] has led to the selection of different algorithms from the same set of candidate ones. This can be an indicator that the performance of recommendation algorithms that have been proved to be performing well in one context (e.g. movie recommendation) should not be expected to do the same in another context (e.g. TEL), an area which requires further experimentation (see Chapter 7).

A different approach to learning resources' recommendation has been followed by Shen and Shen [88]. They have developed a recommender system for learning objects that is based on sequencing rules that help users be guided through the concepts of an ontology of topics. The rules are fired when gaps in the competencies of the learners are identified, and then appropriate resources are proposed to the learners. A pilot study with the students of a Network Education college has taken place, providing feedback regarding the users' opinion about the system.

A similar sequencing system has been introduced by Huang et al. [41]. It uses a Markov chain model to calculate transition probabilities of possible learning objects in a sequenced course of study. The model is supported by an entropy-based approach for discovering one or more recommended learning paths. A pilot implementation has been deployed and tested in a Taiwanese university, involving about 150 users.

Tang and McCalla proposed an evolving e-learning system, open into new learning resources that may be found online, which includes a hybrid recommendation service [89, 90, 91, 92, 93]. Their system is mainly used for storing and sharing research papers and glossary terms among university students and industry practitioners. Resources are described (tagged) according to their content and technical aspects, but learners also provide feedback about them in the form of ratings. Recommendation takes place both by engaging a Clustering Module (using data clustering techniques to group learners with similar interests) and a Collaborative Filtering Module (using classic collaborative filtering techniques to identify learners with similar interests in each cluster). The authors studied several techniques to enhance the performance of their system, such as the usage of artificial (simulated) learners [93]. They have also performed an evaluation study of the system with real learners [94].

A rather simple recommender system without taking into account any preferences or profile information of the learners was applied by Janssen et al. [44]. However, they conducted a large experiment with a control group and an experimental group. They found positive effects on the effectiveness (completion rates of learning objects) though not on efficiency (time taken to complete the learning resources) for the experimental group as compared to the control group.

Nadolski et al. [72] created a simulation environment for different combination of recommendation algorithms in hybrid recommender system in order to compare them against each other regarding their impact on learners in informal learning networks. They compared various cost intensive ontology based recommendation strategies with light-weight collaborative filtering strategies. Therefore, they created treatment groups for the simulation through combining the recommendation techniques in various ways. Nadolski et al. [72] tested which combination of recommendation techniques in recommendation strategies had a higher effect on the learning outcomes of the learners in a learning network. They concluded that the light-weight collaborative filtering recommendation strategies are not as accurate as the ontology-based strategies but worth-while for informal learning networks when considering the environmental conditions like the lack of maintenance in learning networks. This study confirmed that providing recommendations leads towards more effective, more satisfied, and faster goal achievement than no recommendation. Furthermore, their study reveals that a light-weight collaborative filtering recommendation technique including a rating mechanism is a good alternative to maintain intensive top-down ontology recommendation techniques.

Moreover, the ISIS system adopts a hybrid approach for recommending learning resources is the one recently proposed by Hummel et al. [42]. The authors build upon a previous simulation study by Koper [52] in order to propose a system that combines social-based (using data from other learners) with information-based (using metadata from learner profiles and learning activities) in a hybrid recommender system. They also designed an experiment with real learners. Drachsler et al. [28] recently reported the experimental results the ISIS experiment. They found a positive significant effect on efficiency (time taken to complete the learning objects) of the learners after a runtime of four months. It is a very good example of a system that is following the latest trends in learning specifications for representing learner profiles and learning activities.

The same group recently developed a recommender system called ReMashed [26, 27] that addresses learners in informal learning networks. They created a mash-up environment that combines sources of users from different Web2.0 services like Flickr, Delicious.com or Sildeshare.com. Again, they applied a hybrid recommender system that takes advantage of the tag and rating data of the combined Web2.0 sources. The tags that are already given to the Web2.0 sources are used for the cold-start of the recommender system (see Chapter 19). The users of ReMashed are able to rate the emerging data of all users in the system. The ratings are used for classic collaborative filtering recommendations based on the Duine prediction engine [98].

A similar approach is followed by the proposed Learning Object Recommendation Model (LORM) that also follows a hybrid recommendation algorithmic approach and that describes resources upon multiple attributes, but has not yet reported to be implemented in an actual system [95].

Another hybrid recommendation approach has been adopted in the CourseRank system (https://courserank.stanford.edu/CourseRank/main) that is used as an unofficial course guide for Stanford University students. In this system, the recommendation process is viewed under the prism of querying a relational database with course and student information [55]. To this end, a number of tuple ofperators have been defined in order to allow the system to provide flexible recommendations to its users. The system has been first deployed in September 2007, attracting lots of interest from its users: it has been reported that more than 70% of the Stanford students use it [56].

A hybrid approach is also adopted by the prototype system that has been implemented in the course repository of the Virtual University of Tunis (RPL platform, http://cours.uvt.rnu.tn/rpl/). This prototype includes a recommendation engine that combines a collaborative filtering algorithm with a content-based filtering algorithm, using data that has been logged and mined from user actions. The usage logs of the RPL platform are used for this purpose, and a preliminary evaluation experiment has already taken place [49].

Finally, there have been some recent proposals for systems or algorithms that could be used to support recommendation of learning resources. These include a variety of work-in-progress systems, such as a case-based reasoning recommender that Gomez-Albarran and Jimenez-Diaz [33], the contextual recommendations that the knowledge-sharing environment of the APOSDLE EU-project (http://www.aposdle.tugraz.at) offers to the employees of large organisations [1], and the A2M prototype [86]. Recommendation of multimedia learning resource onto mobile devices such as cell phones and PDAs have been explored in [51].

Nevertheless, despite the increasing number of systems proposed for recommending learning resources, a closer look to the current status of their development and evaluation reveals the lack of systematic evaluation studies in the context of real-life applications. As Table 3 indicates:

- More than half of the proposed systems (12 out of 20) still remain at a design or prototyping stage of development;
- Only 10 systems have been reported to be evaluated through trials that involved human users.

Another interesting observation is that, very often, experimental investigation of the recommendation algorithms does not take place. This is a common evaluation practice in systems examined for other domains (e.g. [7, 22, 37, 74]), since careful testing and parameterisation of the algorithms has to be carried out before a recommender system is finally deployed in a real setting (see Chapters 8 and 10). One of the main reasons is that the performance of recommendation algorithms seems to be dependent on the particularities of the application context, therefore, it is advised to experimentally analyse various design choices for a recommender system, before its actual deployment.

12.5 Evaluation of TEL Recommenders

Worthen et al. [111] define evaluation as the “identification, clarification, and application of defensible criteria to determine an evaluation object’s value, quality, utility, effectiveness, or significance in relation to those criteria”. An evaluation of an interactive system ensures that it behaves as expected by the designer and that it meets the requirements of the user [23]. As far as recommender systems in general, and TEL recommenders in particular are concerned, evaluation becomes a critical point at the systems lifecycle for its improvement and success. Until today, evaluation of recommender systems gives emphasis to rather “technical” measures coming from information retrieval research, although the importance of including user-related evaluation methods has been highlighted (see [38, 69] and Chapter 8). In TEL recommender systems evaluation becomes an even more demanding task, considering the particularities of the educational contexts. To this end, we try to provide a first overview of relevant evaluation requirements, adopting the different perspectives covered in this chapter.

Evaluating the different components

The evaluation of AEH systems has generally been considered to be challenging, due to a number of issues that can generally categorised under two types [108]:

- First, adequately defining the reference variables against which the adaptivity of the system will be evaluated is difficult for those systems that either cannot switch off the adaptivity, or where a non-adaptive version appears to be absurd because adaptivity is an inherent feature of these systems [40]. In TEL recommenders, this concerns defining the variables that can successfully measure if switching off the recommendation in a TEL system actually affects its perceived usefulness.

- Second, adequately defined criteria for the success of adaptivity are not well defined or there are rarely commonly accepted criteria: on the one hand, objective standard criteria (e.g. duration, number of interaction steps, knowledge gain) regularly failed to find a difference between adaptive and non-adaptive versions of a system. On the other hand, subjective criteria that are standard in human-computer interaction research (e.g. usability questionnaires) have been rarely applied to measure the success of adaptive systems. In TEL, the issue is related to the definition of appropriate evaluation methods (e.g. techniques, metrics and instruments) to measure the success of a successful recommendation strategy in comparison to a non-successful one.

A common problem arising in such evaluation efforts is when treating the adaptation process as a "monolithic" entity and trying to assess it as a whole [11]. This cannot provide results at a level of granularity that can be of practical use and help the system designer to decide which part of the system needs improvement (e.g. the user modelling approach, the domain modelling approach, the recommendation technique). An interesting approach has been proposed by Brusilovsky et al. [13]: to decompose the adaptation process into two layers that are evaluated separately. The main idea behind the approach was that the evaluation of adaptive systems should not treat adaptation as a "monolithic"/singular process happening behind the scenes. Rather, adaptation should be "broken down" into its constituents, and each of these constituents should be evaluated separately where necessary and feasible [46]. The seeds of this idea can be traced back to Totterdell and Boyle [94] who propose that a number of adaptation metrics could be related to different components of a logical model of adaptive user interfaces, to provide what amounts to adaptation-oriented design feedback. Furthermore, Totterdell and Boyle present two types of assessment performed to validate what is termed "success of the user model" (note that, in their case, the "user model" is also responsible for adaptation decision making):

> *"Two types of assessment were made of the user model: an assessment of the accuracy of the model's inferences about user difficulties; and an assessment of the effectiveness of the changes made at the interface."* [94]

Simultaneously with the idea of evaluating adaptation at two different layers [13], two other *layered* (also referred to as *modular*) evaluation frameworks have been proposed. The process-based framework presented by Weibelzahl [106] consisted from four layers that referred to the information processing steps within the adaptation process: evaluation of input data, evaluation of the inference mechanism, evaluation of the adaptation decision, and evaluation of the total interaction. A second framework has been presented by Paramythis et al. [75] and is more detailed in terms of different components involved in the adaptation process. It also addressed the question of methods and tools appropriate for the evaluation of different adaptation "modules" to yield input for the development process. A merged version of the two frameworks was finally proposed, identifying both criteria to be taken into consideration in the evaluation of an adaptive system, and the methods and tools that can be engaged to do so [109]. This modular evaluation approach has been explored by several studies that evaluate adaptive systems (e.g. [15]), but has not been yet formally developed and applied for recommender systems. It therefore still needs to be validated before applying it into TEL recommender systems. Nevertheless, we believe that this approach can be incorporated in the rich variety of perspectives and measures to be considered when evaluating TEL recommenders. In the following, an initial elaboration on relevant issues is carried out.

Issues to consider for evaluating TEL recommenders

In the world of consumer recommender systems, several data sets with specific characteristics are available (e.g. the MovieLens data set, the Book-Crossing data sets, or the Jester data set). These data sets are used as a common standard or benchmark to evaluate new recommendation algorithms. Furthermore, consumer product recommendation algorithms are evaluated based on common technical measures like accuracy, coverage, and performance in terms of execution time.

In the application domain of TEL, to evaluate pedagogy driven recommender systems for formal or informal learning, no standardised data sets nor standardised evaluation procedures are available. Moreover, focusing only on technical measures for recommender systems in TEL, without considering the actual needs and characteristics of the learners, is questionable. Thus, further evaluation procedures that complement the technical evaluation approaches are needed (see Chapter 8). For example, learners only benefit from TEL supported and enhanced systems when they make the learning more effective, efficient, and/or more attractive. Common measures to evaluate the success of such systems in educational settings thus include *Effectiveness, Efficiency, Satisfaction* and *the Drop-out rate. Effectiveness* is a sign of the total amount of completed, visited or studied content objects during a learning phase. *Efficiency* indicates the time that learners need to reach their learning goal. It is related to the effectiveness variable through counting the actual study time. *Satisfaction* reflects the individual satisfaction of the learners with the given recommendations. Satisfaction is close to the motivation of a learner and therefore an important measure for learning. Finally, the *Drop-out rate* mirrors the numbers of learners that drop out during the learning phase. In educational research the drop-out rate is an important measure when the aim is to graduate as many learners as possible during a learning phase. As far as learning networks are concerned, methods and metrics originating from Social Network Analysis (SNA) (e.g. [105]) could also be engaged to measure the success of TEL recommenders. The SNA measures can be used to estimate the benefits coming from the contributions of the learners for the network as a whole. These are more specific measures that are mainly related to informal learning networks. SNA gives various insights into the different roles learners can have in a learning network. Typical SNA measures are *Variety, Centrality, Closeness* and *Cohesion*. *Variety* measures the level of emergence in a learning network through the combination of individual learning paths to the most successful learning routes. *Centrality* is an indicator for the connectivity of a learner in a learning network. It counts the number of ties to other learners in the network. *Closeness* measures the degree a learner is close to all other learners in a network. It represents the ability to access information direct or indirect through the connection to other network members. *Cohesion*, on the other hand, indicates how strongly learners are directly connected to each other by cohesive bonds. Peer-groups of learners can be identified if every learner is directly tied to every other learner in the learning network. Drachsler et al. [24] followed this approach by using simulations to evaluate the impacts of a recommender system for learners in informal learning networks (see Chapter 18).

Synthesising all the various components into an overall evaluation framework has several methodological and practical difficulties. As a general guideline, however, classical evaluation frameworks from educational research could be adopted and adapted to the recommender systems' context. As an example, we illustrate how the Kirckpatrick's model [50], which measures the success of training using four different layers, could be used to evaluate the success of a recommender system in a TEL context:

1. **Reaction** of user - what they thought and felt (*"Did I enjoy the recommendations I receive?"*);
2. **Learning** - the resulting increase in gaining new knowledge or capabilities (*"Did I learn what I needed to and get some new ideas, with the help of the recommender?"*);
3. **Behaviour** - extent of how acquired knowledge and capability can be implemented/applied in real life (*"Will I use the new information and ideas I was recommended?"*);
4. **Results** - the effects on the user's performance in the learning or working environment (*"Do the ideas and information I was recommended improve my effectiveness and results?"*).

Therefore, the definition of an overall evaluation framework of TEL recommenders could include:

- A detailed analysis of the evaluation methods and tools that can be employed for evaluating TEL recommendation techniques against a set of criteria that will be proposed for each of the selected components (e.g. user model, domain model, recommendation strategy and algorithm). For the presented example of the Kirckpatrick's dimensions, this would include an identification of the evaluation methods that could be engaged to measure the effect of the recommender in a particular TEL context, upon each one of the four dimensions.
- The specification of evaluation metrics/indicators to measure the success of each component (e.g. evaluating accuracy of the recommendation algorithm,

evaluating coverage of the domain model). For the presented example, this would include a specification of the particular metrics that can measure the effect of introducing the recommender in this TEL context.
- The elaboration of a number of methods and instruments that can be engaged in TEL settings, in order to collect evaluation data from engaged stakeholders, explicitly or implicitly, e.g. measuring user satisfaction, assessing impact of engaging the TEL recommender from improvements in working tasks. For the presented example, this would include the proposal of specific instruments that can be used to measure each one of the metrics that measure the effect of introducing the recommender in this TEL context.

12.6 Conclusions and further work

This chapter provides an introduction to the issues related to the deployment of recommender systems in the Technology Enhanced Learning (TEL) settings emphasising the particularities of this application domain. It first discussed the context in which TEL recommenders are deployed, and reflected on related user tasks and recommendation goals. A review of related work coming from the research strands of Adaptive Educational Hypermedia and Learning Networks has been provided, with a particular emphasis on how it applies to TEL recommenders for formal and informal settings. Then, a survey of TEL recommenders proposed in the literature was presented with a critical view on the actual implementation of systems. Particular emphasis was given to the evaluation leading to a discussion on evaluation requirements and issues for TEL recommender systems. To our knowledge, this is the first study attempting to systematically cover the design and deployment of recommender systems in the TEL settings (see Chapter 11). Nevertheless, it can only provide a brief overview of related issues, leaving several aspects to be further explored and researched.

As indicated in the previous section, one of the main research challenges related to the introduction of recommender systems in TEL is how to perform a systematic development and evaluation of such systems and their effect. To this end, a systematic analysis of TEL-related tasks that can be supported by recommender systems took place, in order to identify the particular requirements that need to be considered. Furthermore, the development of concrete evaluation frameworks that will follow a layered approach is an open issue. These frameworks can focus on incorporating as many evaluation dimensions as possible, also addressing pedagogical dimensions, by combining a variety of evaluation methods, metric, and instruments.

In addition, for the various groups of researchers involved in TEL, a number of topics are of high research interest. For example, the recommendation support for learners in formal and informal learning that takes advantage of contextualised recommender systems has become an important one. These recommender systems, also called context-aware recommender systems (see [61] and Chapter 7), use for example geographical location of a user to recommend relevant resources. Such contextualisation becomes important, for example, when multilingual educational resources are recommended from a number of repositories residing in different countries and complying with various curricula requirements [101]. Additionally, context awareness could include pedagogical aspects like prior knowledge, learning goals or study time to embed pedagogical reasoning into collaborative filtering driven recommendations.

Another promising approach is the use of multi-criteria input for recommender system in TEL (see Chapter 24). Users (learners and teachers) can not only rate learning resource based on the level of complexity, curriculum alignment or how much time is required to cover the learning material, but input could also be inferred from different implicit sources. Such multidimensional input can potentially have a high impact on the suitability of recommendations. A related problem is the lack of TEL specific rated data sets for informal and formal learning. Different to the recommender system world, where many data sets are available (e.g. MovieLens, BookCrossing, Jester Collaborative Filtering Dataset), the TEL community is still working with rather small home-made data sets, which are rarely public available [66].

Acknowledgements

Research of N. Manouselis was funded with support by the European Commission and more specifically, the project ECP-2006-EDU-410012 'Organic.Edunet: A Multilingual Federation of Learning Repositories with Quality Content for the Awareness and Education of European Youth about Organic Agriculture and Agroecology' of the *e*Content*plus* Programme. Research of H. Drachsler was funded with support by the European Commission and more specifically, the project IST 027087 'TEN-Competence' of the FP6 Programme. Riina Vuorikari thanks the HS-säätiö for the stipend.

References

1. Aehnelt M., Ebert M. Beham G., Lindstaedt S., Paschen A.: A Socio-technical Approach towards Supporting Intra-organizational Collaboration. In: Dillenbourg P. and Sprecht M., (eds.) Times of convergence: Technologies across learning contexts. Proceedings of the 3rd European Conference on Technology Enhanced Learning (EC-TEL 2008), Maastricht, The Netherlands, LNCS 5192, pp. 33-38, Berlin: Springer (2008).
2. Anderson M., Ball M., Boley H., Greene S., Howse N., Lemire D., McGrath S.: RACOFI: A Rule-Applying Collaborative Filtering System. Paper presented at the conference IEEE/WIC COLA 2003, 13 October, Halifax, Canada.
3. Aroyo, L., Mizoguchi, R., and Tzolov, C.: OntoAIMS- Ontological Approach to Courseware Authoring. Paper presented at the International Conference on Computers in Education (ICCE 2003), 2-5 December, Hong Kong, China

4. Avancini H., Straccia U.: User recommendation for collaborative and personalised digital archives, International Journal of Web Based Communities **1**(2), 163–175 (2005).
5. Baldoni, M., Baroglio, C., Brunkhorst, I., Marengo, E., Patti, V.: Reasoning-Based Curriculum Sequencing and Validation: Integration in a Service-Oriented Architecture. In Proceedings of the 2^{nd} European Conference on Technology Enhanced Learning (EC-TEL 2007), LNCS 4753, pp. 426. Berlin: Springer (2007).
6. Baudisch P.: Dynamic Information Filtering. PhD Thesis, GMD Forschungszentrum Informationstechnik GmbH, Sankt Augustin (2001).
7. Breese, J. S., Heckerman, D., and Kadie, C.: Empirical analysis of predictive algorithms for collaborative filtering. In: Cooper G. F. and Moral S., (eds.) Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence (UAI-98), pp. 43-52, Morgan-Kaufmann, Californian, San Francisco (1998).
8. Brockett, R. G., & Hiemstra, R.: Self-direction in adult learning: perspectives on theory, research, and practice. London: Routledge (1991).
9. Brusilovsky, P.: Methods and techniques of adaptive hypermedia, User Modeling and User-Adapted Interaction **6**(2-3), 87–129 (1996).
10. Brusilovsky, P.: Adaptive hypermedia. User Modeling and User-Adapted Interaction **11**(1-2), 87–110 (2001).
11. Brusilovsky, P. and Eklund, J.: A study of user-model based link annotation in educational hypermedia, Journal of Universal Computer Science **4**(4), 429–448 (1998).
12. Brusilovsky P., Nejdl W.: Adaptive Hypermedia and Adaptive Web. Practical Handbook of Internet Computing, Chapman & Hall / CRC Press LLC (2005).
13. Brusilovsky, P., Karagiannidis, C., and Sampson, D. G.: The benefits of layered evaluation of adaptive applications and services. In: Weibelzahl, S., Chin, D. N., and Weber, G. (eds.) Empirical Evaluation of Adaptive Systems. Proceedings of 8th International Conference on User Modeling, (UM2001), pp 1-8, Berlin: Springer (2001).
14. Brusilovsky, P., Pesin, L., & Zyryanov, M.: Towards an adaptive hypermedia component for an intelligent learning environment. In: Bass, L.J., Gornostaev, J., & Unger, C. (eds.) Human-Computer Interaction (LNCS 753). pp. 348-358, Berlin: Springer (1993).
15. Brusilovsky P., Karagiannidis C., Sampson D., Layered evaluation of adaptive learning systems. International Journal of Continuing Engineering Education and Lifelong Learning **14**(4/5), 402–421 (2004).
16. Brusilovsky, P., & Henze, N.: Open Corpus Adaptive Educational Hypermedia. In P. Brusilovsky, A. Kobsa & W. Nejdl (eds.) The Adaptive Web: Methods and Strategies of Web Personalization. (LNCS 4321), pp. 671-696 Berlin: Springer (2007).
17. Colley, H., Hodkinson, P., & Malcolm, J.: Non-formal learning: mapping the conceptual terrain. A consultation report. (2008). Accessed 11 January 2010.
18. Cristea, A.: Authoring of Adaptive Hypermedia. Educational Technology & Society **8**(3), 6–8 (2005).
19. De Bra, P. M. E.: Teaching Hypertext and Hypermedia through the Web. Journal of Universal Computer Science **2**(12), 797–804 (1996).
20. De Bra, P., Aerts, A., Smits, D., & Stash, N.: AHA! Version 2.0, More Adaptation Flexibility for Authors. Paper presented at the World Conference on e-Learning in Corporate, Government, Healthcare & Higher Education. 15-19 October 2002, Montreal, Canada (2002).
21. De La Passardiere, B., & Dufresne, A.: Adaptive navigational tools for educational hypermedia. In: I. Tomek (ed.), Computer Assisted Learning. Proceedings of the 4th International Conference on Computers and Learning (ICCAL'92), LNCS 602, pp. 555-567, Berlin: Springer (1992).
22. Deshpande, M., & Karypis, G.: Selective Markov models for predicting Web page accesses. Transactions on Internet Technology. **4**(2), 163–184 (2004).
23. Dix, A. J., Finlay, J. E., Abowd, G. D., and Beale, R.: Human-Computer Interaction. Harlow, England: Prentice Hall (1998).

24. Drachsler H., Hummel H. G. K., Koper R.: Personal recommender systems for learners in lifelong learning: requirements, techniques and model. International Journal of Learning Technology **3**(4), 404–423 (2008a).
25. Drachsler, H., Hummel, H.G.K., Koper, R..: Using Simulations to Evaluate the Effects of Recommender Systems for Learners in Informal Learning Networks. In: Vuorikari, R., Kieslinger, B., Klamma, R., Duval, E. (eds.): SIRTEL workshop at the 3rd EC-TEL conference. CEUR Workshop Proceedings VOL-382, Maastricht, The Netherlands (2008b).
26. Drachsler, 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, Proceedings of the 4^{th} European Conference on Technology Enhanced Learning (EC-TEL 2009), LNCS 5794, pp. 788-793, Berlin: Springer (2009a).
27. Drachsler, H., Pecceu, D., Arts, T., Hutten, E., Rutledge, L., Van Rosmalen, P., Hummel, H.G.K., Koper, R.: ReMashed-An Usability Study of a Recommender System for Mash-Ups for Learning. 1st Workshop on Mashups for Learning at the International Conference on Interactive Computer Aided Learning, Villach, Austria (2009b).
28. Drachsler, H., Hummel, H. G. K., Van den Berg, B., Eshuis, J., Berlanga, A., Nadolski, R., Waterink, W., Boers, N., & Koper, R..: Effects of the ISIS Recommender System for navigation support in self-organized learning networks. Journal of Educational Technology and Society **12**, 122–135 (2009c).
29. Dron, J., Mitchell, R., Boyne, C., & Siviter, P.: CoFIND: steps towards a self-organising learning environment. Proceedings of the World Conference on the WWW and Internet (WebNet 2000), San Antonio, Texas, USA, October 30-November 4, pp. 146-151, USA AACE (2000a).
30. Dron, J., Mitchell, R., Siviter, P., & Boyne, C.: CoFIND-an experiment in n-dimensional collaborative filtering. Journal of Network and Computer Applications **23**(2), 131–142 (2000b).
31. Duval E., Vuorikari R., Manouselis N. (Eds.), Special Issue on Social Information Retrieval in Technology Enhanced Learning, Journal of Digital Information (JoDI), Vol. 10, (2009).
32. Fiaidhi J.: RecoSearch: A Model for Collaboratively Filtering Java Learning Objects. International Journal of Instructional Technology and Distance Learning **1**(7), 35–50 (2004).
33. Gomez-Albarran M., Jimenez-Diaz G.: Recommendation and Students' Authoring in Repositories of Learning Objects: A Case-Based Reasoning Approach. International Journal of Emerging Technologies in Learning (iJET) **4**(1), 35–40 (2009).
34. Gonschorek, M., & Herzog, C.: Using hypertext for an adaptive helpsystem in an intelligent tutoring system. In: J. Greer (Ed.), Artificial Intelligence in Education, Proceedings of the 7th World Conference on Artificial Intelligence in Education, (AI-ED'95), 16-19 August, Washington, DC, AACE, pp. 274 (1995).
35. Gordon, D.: Ants at Work: How an Insect Society is Organized. Free Press, New York (1999).
36. Graham, A.: Blended learning systems: definitions, current trends and future directions. In: Bonk, C. J. & Graham, C. R. (eds.) Handbook of blended learning: Global Perspectives, local designs. San Francisco, CA: Pfeiffer Publishing, pp. 3-21 (2005).
37. Herlocker, J., Konstan, J., Riedl, J.: An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms. Information Retrieval **5**(4), 287–310 (2002).
38. Herlocker, J.L., Konstan, J.A., Terveen, L.G., & Riedl, J.T.: Evaluating Collaborative Filtering Recommender Systems. ACM Transactions on Information Systems **22**(1), 5–53 (2004).
39. Hohl, H., Böcker, H.-D., Gunzenhäuser, R.: Hypadapter: An adaptive hypertext system for exploratory learning and programming. User Modeling and User-Adapted Interaction **6**(2-3), 131–156 (1996).
40. Höök, K.: Steps to take before intelligent user interfaces become real. Interacting With Computers **12**(4), 409–426 (2000).

41. Huang, Y.-M., Huang, T.-C., Wang, K.-T., Hwang, W.-Y.: A Markov-based Recommendation Model for Exploring the Transfer of Learning on the Web. Educational Technology & Society **12**(2), 144–162 (2009).
42. Hummel, H.G.K., Van den Berg, B., Berlanga, A.J., Drachsler, H., Janssen, J., Nadolski, R.J., Koper, E.J.R.: Combining Social- and Information-based Approaches for Personalised Recommendation on Sequencing Learning Activities. International Journal of Learning Technology **3**(2), 152–168 (2007).
43. Jameson, A.: Systems That Adapt to Their Users: An Integrative Perspective. Saar-brücken: Saarland University (2001).
44. Janssen, J., Tattersall, C., Waterink, W., Van den Berg, B., Van Es, R., Bolman, C., et al.: Self-organising navigational support in lifelong learning: how predecessors can lead the way. Computers & Education **49**, 781–793 (2005).
45. Johnson, S.: Emergence. Scribner, New York (2001).
46. Karagiannidis, C., Sampson, D. G.: Layered evaluation of adaptive applications and services. In: Brusilovsky, P. and Stock, C. S. O. (Eds.), Proc. of International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems, AH2000, Trento, Italy, pp. 343-346. Berlin: Springer (2000).
47. Karampiperis, P., Sampson, D.: Adaptive Learning Resources Sequencing in Educational Hypermedia Systems. Educational Technology & Society **8**(4), 128–147 (2005).
48. Kay, J., Kummerfeld, R. J.: An individualised course for the C programming language. In: Proceedings of Second International WWW Conference. Chicago, USA (1994).
49. Khribi, M.K., Jemni, M., Nasraoui, O.: Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and Information Retrieval. Educational Technology & Society **12**(4), 30–42 (2009).
50. Kirkpatrick, D.L.: Evaluating Training Programs (2nd ed.). Berrett Koehler, San Francisco (1959).
51. Klamma, R., Spaniol, M., Cao, Y.: Community Aware Content Adaptation for Mobile Technology Enhanced Learning. In: Innovative Approaches for Learning and Knowledge Sharing, pp. 227-241 (2006).
52. Koper, R.: Increasing Learner Retention in a Simulated learning network using Indirect Social Interaction. Journal of Artificial Societies and Social Simulation, **8**(2) (2005).
53. Koper, E.J.R., Tattersall, C.: New directions for lifelong learning using network technologies. British Journal of Educational Technology **35**(6), 689–700 (2004).
54. Koper, R., Rusman, E., & Sloep, P.: Effective Learning Networks. Lifelong Learning in Europe **1**, 18–27 (2005).
55. Koutrika, G., Ikeda, R., Bercovitz, B., Garcia-Molina, H.: Flexible Recommendations over Rich Data. In: Proc. of the 2nd ACM International Conference on Recommender Systems (Rec-Sys'08). Lausanne, Switzerland, (2008).
56. Koutrika, G., Bercovitz, B., Kaliszan, F., Liou, H., Garcia-Molina, H.: CourseRank: A Closed-Community Social System Through the Magnifying Glass. In: Proc. of the 3rd International AAAI Conference on Weblogs and Social Media (ICWSM'09). San Jose, California (2009).
57. Kravcik, M., Specht, M., Oppermann, R.: Evaluation of WINDS Authoring Environment. In: P. De Bra & W. Nejdl (Eds.), Adaptive Hypermedia and Adaptive Web-Based Systems, LNCS **3137**, 166–175). Berlin: Springer (2004).
58. Krulwich, B.: Lifestyle Finder: Intelligent User Profiling Using Large-Scale Demographic Data. Artificial Intelligence Magazine **18**(2), 37–45 (1997).
59. Kumar, V., Nesbit, J., Han, K.: Rating Learning Object Quality with Distributed Bayesian Belief Networks: The Why and the How. In: Proc. of the Fifth IEEE International Conference on Advanced Learning Technologies, ICALT'05 (2005).
60. Lemire, D.: Scale and Translation Invariant Collaborative Filtering Systems. Journal of Information Retrieval **8**(1), 129–150 (2005).

61. 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) (2005).
62. Liber, O.: Colloquia - a conversation manager. Campus-Wide Information Systems **17**, 56–61 (2000).
63. Liber, O., Johnson, M. (2008). Personal Learning Environments. Interactive Learning Environments **16**, 1–2 (2008).
64. Longworth, N.: Lifelong learning in action - Transforming education in the 21st century. Kogan Page, London (2003).
65. Manouselis, N., Costopoulou, C.: Experimental Analysis of Design Choices in Multi-Attribute Utility Collaborative Filtering. International Journal of Pattern Recognition and Artificial Intelligence, Special Issue on Personalization Techniques for Recommender Systems and Intelligent User Interfaces **21**(2), 311–331 (2007).
66. Manouselis, N., Vuorikari, R.: What if annotations were reusable: a preliminary discussion. In: Proc. of the 8th International Conference on Web-based Learning (ICWL 2009). Aachen, Germany (2009).
67. Manouselis, N., Vuorikari, R., Van Assche, F.: Simulated Analysis of MAUT Collaborative Filtering for Learning Object Recommendation. In: Proc. of the Workshop on Social Information Retrieval in Technology Enhanced Learning (SIRTEL 2007). Crete, Greece (2007).
68. McCalla, G.: The Ecological Approach to the Design of E-Learning Environments: Purpose-based Capture and Use of Information About Learners. Journal of Interactive Media in Education, Special Issue on the Educational Semantic Web, **7**, ISSN:1365-893X (2004).
69. McNee, S.: Meeting User Information Needs in Recommender Systems. Doctoral dissertation, University of Minnesota-Twin Cities, Minneapolis, MN, USA (2006).
70. Moore, J.D., Swartout, W.R.: Pointing: A way toward explanation dialogue. In: Proceedings of the Eighth National Conference on Artificial Intelligence, pp. 457-464. AAAI (1990).
71. Moore, M.G., Anderson, W.G.: Handbook of distance education. Lawrence Erlbaum, Mahwah N.J. (2004).
72. Nadolski, R.J., Van den Berg, B., Berlanga, A., Drachsler, H., Hummel, H., Koper, R., Sloep, P.: Simulating Light-Weight Personalised Recommender Systems in Learning Networks: A Case for Pedagogy-Oriented and Rating-Based Hybrid Recommendation Strategies. Journal of Artificial Societies and Social Simulation (JASSS), **12**(14) (2009).
73. Oppermann, R.: Adaptively supported adaptability. Int. J. Hum.-Comput. Stud. **40**(3), 455–472 (1994).
74. Papagelis, M., Plexousakis, D., Kutsuras, T.: Alleviating the Sparsity Problem of Collaborative Filtering Using Trust Inferences. In: Proceedings of the 3rd International Conference on Trust Management, pp. 224-239. Springer (2005).
75. Paramythis, A., Totter, A., Stephanidis, C.: A modular approach to the evaluation of adaptive user interfaces. In Weibelzahl, S., Chin, D., Weber, G. (eds.) Empirical Evaluation of Adaptive Systems. Proceedings of workshop at the Eighth International Conference on User Modeling, UM2001, pp. 9-24. Freiburg (2001).
76. Paris, C.: Tailoring object description to a user's level of expertise. Computational Linguistics **14**(3), 64–78 (1988).
77. Pérez, T., Gutiérrez, J., Lopistéguy, P.: An adaptive hypermedia system. In: Proceedings of AI-ED'95, 7th World Conference on Artificial Intelligence in Education, pp. 351-358. AACE (1995).
78. Rafaeli, S., Barak, M., Dan-Gur, Y., Toch, E.: QSIA-a Web-based environment for learning, assessing and knowledge sharing in communities. Computers, Education **43**(3), 273–289 (2004).
79. Rafaeli , S., Dan-Gur , Y., Barak , M.: Social Recommender Systems: Recommendations in Support of E-Learning. International Journal of Distance Education Technologies **3**(2), 29–45 (2005).
80. Recker, M.M., Walker, A.: Supporting "Word-of-Mouth" Social Networks through Collaborative Information Filtering. Journal of Interactive Learning Research **14**(1), 79–99 (2003).

81. Recker, M.M., Wiley, D.A.: A non-authoritative educational metadata ontology for filtering and recommending learning objects. Interactive learning environments **9**(3), 255–271 (2001).
82. Recker, M.M., Walker, A., Wiley, D.: An interface for collaborative filtering of educational resources. In: International Conference on Artificial Intelligence, pp. 26-29. Las Vegas, Nevada, USA (2000).
83. Recker, M.M., Walker, A., Lawless, K.: What do you recommend? Implementation and analyses of collaborative information filtering of web resources for education. Instructional Science **31**(4/5), 299–316 (2003).
84. Rokach, L., Maimon, O., Averbuch, M., Information Retrieval System for Medical Narrative Reports, Lecture Notes in Artificial intelligence 3055, page 217-228 Springer-Verlag (2004)
85. Rokach, L., Maimon, O., Arbel, R., Selective voting-getting more for less in sensor fusion, International Journal of Pattern Recognition and Artificial Intelligence 20 (3), pp. 329–350 (2006)
86. Santos, O.C.: A recommender system to provide adaptive and inclusive standard-based support along the eLearning life cycle. In: Proceedings of the 2008 ACM conference on Recommender systems, pp. 319-322 (2008).
87. Schneider-Hufschmidt, M., Kuhme, T., Malinowski, U.: Adaptive User Interfaces: Principles and Practice. Elsevier Science Inc (1993).
88. Shen, L., Shen, R.: Learning content recommendation service based-on simple sequencing specification. In: Liu W et al. (eds), pp. 363-370. Lecture notes in computer science (2004).
89. Tang T., McCalla G.: Smart Recommendation for an Evolving E-Learning System. In: Proc. of the Workshop on Technologies for Electronic Documents for Supporting Learning, International Conference on Artificial Intelligence in Education (AIED 2003) (2003).
90. Tang, T., McCalla, G.: Utilizing Artificial Learner on the Cold-Start Pedagogical-Value based Paper Recommendation. In: Proc. of AH 2004: International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems (2004a).
91. Tang, T., McCalla, G.: Beyond Learners' Interest: Personalized Paper Recommendation Based on Their Pedagogical Features for an e-Learning System. In: Proceedings of the 8th Pacific Rim International Conference on Artificial Intelligence (PRICAI 2004), pp. 301-310 (2004b).
92. Tang, T.Y., McCalla, G.: On the pedagogically guided paper recommendation for an evolving web-based learning system. In: Proceedings of the 17th International FLAIRS Conference, pp. 86-91 (2004c).
93. Tang, T., McCalla, G.: Smart Recommendation for an Evolving E-Learning System: Architecture and Experiment. International Journal on E-Learning **4**(1), 105–129 (2005).
94. Totterdell, P., Boyle, E.: The evaluation of adaptive systems. Adaptive User Interfaces 161-194 (1990).
95. Tsai, K.H., Chiu T.K., Lee M.C., Wang T.I.: A learning objects recommendation model based on the preference and ontological approaches. In: Proc. of 6th International Conference on Advanced Learning Technologies (ICALT'06). IEEE Computer Society Press (2006).
96. Tzikopoulos, A., Manouselis, N., Vuorikari, R.: An overview of Learning Object Repositories. In: Learning Objects for Instruction, Design and Evaluation, pp. 29-55. Idea Group Publishing, Hershey, PA (2007).
97. Van Bruggen, J., Sloep, P., van Rosmalen, P., Brouns, F., Vogten, H., Koper, R., Tattersall, C.: Latent semantic analysis as a tool for learner positioning in learning networks for lifelong learning. British Journal of Educational Technology **35**(6), 729–738 (2004).
98. Van Setten, M.: Supporting people in finding information: hybrid recommender systems and goal-based structuring. Telematica Instituut Fundamental Research Series NO. 016 (TI/FRS/016). Enschede, The Netherlands (2005).
99. Vuorikari, R., Berendt, B.: Study on contexts in tracking usage and attention metadata in multilingual Technology Enhanced Learning. In: Fischer, S., Maehle, E., Reischuk, R. (eds.) Im Focus das Leben, pp. 181, 1654-1663. Lecture Notes in Informatics (2009).

100. Vuorikari, R., Koper, R.: Ecology of social search for learning resources. Campus-Wide Information Systems **26**(4), 272–286 (2009).
101. Vuorikari, R., Ochoa, X.: Exploratory Analysis of the Main Characteristics of Tags and Tagging of Educational Resources in a Multi-lingual Context. Journal of Digital Information **10**(2) (2009).
102. Vygotsky, L.: Mind in Society: The Development of Higher Psychological Processes. Harvard University Press (1978).
103. Waldrop, M.: Complexity: The Emerging Science at the Edge of Order and Chaos. Simons, Schuster, New York (1992).
104. Walker, A., Recker, M., Lawless, K., Wiley, D.: Collaborative information filtering: A review and an educational application. International Journal of Artificial Intelligence in Education **14**(1), 3–28 (2004).
105. Wasserman, S., Faust, K.: Social network analysis: Methods and applications. Cambridge Univ Pr (1994).
106. Weibelzahl, S.: Evaluation of adaptive systems. In: User Modeling: Proceedings of the Eighth International Conference, UM2001, pp. 292-294 (2001).
107. Weibelzahl, S. Evaluation of adaptive systems. PhD dissertation. University of Trier, Germany (2003).
108. Weibelzahl, S., Paramythis, A., Totter, A.: A layered framework for the evaluation of interactive adaptive systems. In: Proc. 2nd Workshop on Empirical Evaluation of Adaptive Systems. Johnstown (2003).
109. Wild, F., Mödritscher, F., Sigurdarson, S.E.: Designing for change: mash-up personal learning environments. eLearning Papers. **9** (2008).
110. Wilson, S., Sharples, P., Griffiths, D.: Distributing education services to personal and institutional systems using Widgets. In: Mash-Up Personal Learning environments, Proceedings of the 1st MUPPLE workshop. CEUR-Proceedings (2008).
111. Worthen, B.R., Sanders, J.R., Fitzpatrick, J.L.: Program evaluation. Longman, New York (1997).