

Towards a Viewpoint of Recommender Systems and Techniques in Technology Enhanced Learning (TEL)

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ABSTRACT

Technology Enhanced learning (TEL) is a learning process or activity that aims to develop, design and test socio-technical innovations that will support and enhance learning practices of both individuals and organisations. TEL is an application domain that generally addresses all types of technology research and development aiming to support teaching and learning activities. Recommender systems, methods and techniques open an interesting new approach to facilitate and support academic learning and teaching. Information retrieval through Recommender Systems is a pivotal activity in TEL, and the deployment of recommender systems has attracted increased interest during the past years. With a focus on user (learner) framework, we review the importance of recommender systems, methods and techniques in TEL through relevant literature of existing research and also discuss relevant open research issues of recommender systems, methods and techniques in TEL.

Keywords: Technology Enhanced Learning (TEL), Recommender Systems, Collaborative Filtering, Content-Based Filtering, Information and Communication Technology (ICT), Teaching, Learners, Technology Acceptance Model (TAM)

I. 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 an application domain that generally addresses all types of technology research & development aiming to support teaching and learning activities [1-4, 48]. Information retrieval is a pivotal activity in Technology Enhanced Learning (TEL), and the deployment of recommender systems has attracted increased interest during the past years. Recommendation methods, techniques and systems open an interesting new approach to facilitate and support learning and teaching. There are plenty of resources available on the web, both in terms of digital learning contents and people resources (e.g. other learners, experts, tutors) that can be used to facilitate teaching and learning tasks

[1-4, 48]. The challenge is to develop, deploy and evaluate systems that provide learners and teachers with meaningful guidance in order to help identify suitable learning resources from a potentially overwhelming variety of choices. Personal recommender systems strongly depend on the context or domain they operate in, and it is often not possible to take one recommender system from one context and transfer it to another context or domain [1-4, 48]. This paper describes a number of distinct differences for personalized recommendation to consumers of commercial products in contrast to recommendations to learners. Similarities and differences are translated into specific demands for learning and specific requirements for personal recommendation systems [1-4]. This paper analyses recommender systems, methods and techniques that provide pedagogically reasonable recommendations to learners. There is an increasing use of *Recommender Systems (RS)* that support users in finding their way through the possibilities on offer in the Internet. For instance, the well-known company amazon.com [5] is using a recommender system to direct the attention of their costumers to other products in their collection. The main purpose of recommender systems is to pre-select information a user might be interested in. Existing 'way finding services' may inspire and help us when designing and developing specific recommender systems for lifelong learning as well as TEL [2-3, 48]. The rest of the paper is as follows: Our Research Objectives and Research Methodology are discussed in Sections II and III respectively. We Review Literature in Section IV. We elaborate on the Existing Research of Recommender Systems in Technology Enhanced Learning (TEL) in Section V and discuss relevant Open Research issues of Recommender Systems in Technology Enhanced Learning (TEL) in Section VI. We finally conclude the paper with a recommendation in Section VIII.

II. RESEARCH OBJECTIVES

The main objectives of this research paper are to:

- Discuss the importance of recommender systems, methods and techniques in Technology Enhanced Learning (TEL).
- Review ICT in education from a perspective of recommender systems, methods and techniques in Technology Enhanced Learning (TEL).

III. RESEARCH METHODOLOGY

- **Literature Review:** We adopted integrated and exploratory literature about current ICT trends in education (teaching and learning), recommender systems, methods and techniques in Technology Enhanced Learning (TEL).

IV. LITERATURE REVIEW

A. Background of Technology Acceptance Model (TAM) The introduction of various Information and Communication Technologies (ICTs) is reducing geographical constraints and changing interpersonal communication dynamics. Information and Communication Technology (ICT) is also dramatically affecting the way people teach and learn [6]. As new Information and Communication Technologies (ICTs) infiltrate workplaces, homes, and classrooms, research on user acceptance of new technologies has started to receive much attention from professionals as well as academic researchers [6]. ICT Developers and software industries are beginning to realize that lack of user acceptance of technology can lead to loss of money and resources [6]. Afari and Achampong [6] cited and discussed that the Technology Acceptance Model (TAM) has received great respect in the Information and Communication Technology (ICT) and Information Systems (IS) literature [7][8]. The key purpose of TAM is to trace the impact of external variables on internal beliefs, attitudes, and intentions. The TAM focuses on information systems use. The model is illustrated in figure 1.

Perceived Usefulness (PU) - This was defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” [7].

Perceived Ease-Of-Use (PEOU) was defined as “the degree to which a person believes that using a particular system would be free from effort” [7]. These factors play a crucial role in understanding individual responses to ICT [9][10][11]. Research over the past decade provides evidence of the significant effect perceived ease of use has on usage intention [12-14].

According to TAM, *Usefulness (U)* and *Ease of Use (EOU)* have a significant impact on a *User's Attitude (A)* toward using a system (i.e. the feelings of favourableness or unfavourableness toward the system).

Behavioral Intentions (BI) to use a system are modeled as a function of *A* and *U*. *BI* then determines actual use. Research has consistently shown that *BI* is the strongest predictor of actual use [7].

1. The Concept of User Acceptance

User acceptance is defined as “the demonstrable willingness within a user group to employ Information and Communication Technology (ICT) for the tasks it is designed to support” [14]. The concept does not apply to situations in which users claim they will utilize technology without providing evidence of use, or where they use the technology for purposes unintended by the designers or those who acquired it (e.g., using an Internet connection for personal chatting in a work situation). Lack of user acceptance is a significant impediment to the success of new information systems [15][16]. User acceptance is therefore a pivotal factor in determining the success or failure of any information systems project such as Technology Enhanced Learning [17].

2. User Experience and Technology Acceptance

Researchers using the Technology Acceptance Model (TAM) have proposed that an individual's experiences with a specific technology influence perceptions of ease of use and usefulness of that technology.

A study examining employee adoption of a new workstation operating system found that an individual's previous computer experience positively influenced perceptions of ease of use and usefulness [12].

Venkatesh and Davis [14] reported that users' experience influenced the relationship between model components and intentions. Experience may therefore be an important consideration in application of technological models.

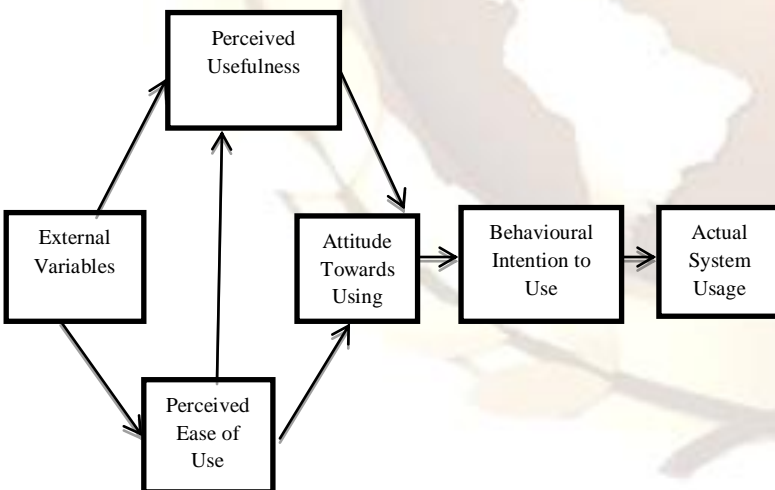


Fig. 1. Technology Acceptance Model (TAM) Source: (Davis et al., 1989, p985) [6]

The Technology Acceptance Model (TAM) suggests that when users are presented with a new technological system involving ICT hardware and software, a number of factors influence their decision about how and when they will use it, notably:

An empirical study examining microcomputer usage found evidence that users' computer experience influenced perceptions of ease of use, usefulness and usage [18]. Several studies including Macharia and Nyakwende [19] have proposed that, distinction had to be made between the various factors that influence adoption and diffusion of information systems including individual (Yang and Jolly) [20] environmental (Gong et al.) [21], organizational factors (Seyal et al.) [22] and technical (Sheng et al.) [23].

An empirical, longitudinal study examining e-mail usage of graduate business students suggested that as a user becomes more experienced with a technology, perceptions of usefulness directly determines intention of use and usage [24].

B. Background of Technology Enhanced Learning (TEL) Modes of educational involving e-learning or m-learning or blended learning (traditional or distance learning combined with ICT) is intimately connected with and dependent on the human cognitive system and technology. Mobile learning involves learning by teachers and students through the use of mobile devices such as Personal Digital Assistants (PDAs), mobile phones and Smartphones [25-27]. E-learning involves the use of Desktop Personal Computers (PCs) for learning and teaching activities of teachers and students [28-31]. Learning means that the cognitive system acquires information and stores it for further use. If these processes do not operate/occur properly, then the learners will not initially acquire the information, and even if they do, then they will not be able to recall it later, and/or the learning information will not be utilised and behaviour will not be modified [32].

Irrespective of whether the objective is learning new information (e.g., environmental regulations, good specifications, etc.), acquiring new skills (e.g., operating a new experimental setup, customer service, financial management, time management, etc.), or knowledge sharing and transfer within or across organisations — the processes of acquiring, storing and applying the learning information are critical [32].

A research question in [32] was how to achieve these cornerstone processes of acquiring, storing and applying of learning information and whether technology can enhance them. According to [32], the answer is clear: Learning must fit human cognition. There is a lot of scientific knowledge and research on human cognition and learning. The difficult and problematic challenge is how to translate this theoretical and academic research into practical ways to utilise technology so as to enhance learning. By bridging basic research about learning and the brain into ways of using learning

technologies, one is able to create sophisticated learning programmes [32].

C.Importance of Recommender Systems and Techniques in Technology Enhanced Learning (TEL)

Recommender Systems apply knowledge discovery techniques to the problem of making/generating personalized recommendations for information, products or services during a live interaction [33]. The tremendous growth in the amount of available information and the number of visitors of websites in recent years possess a key challenge for recommender systems. Some of these challenges are: producing high quality recommendations, performing many recommendations per second for millions of users and items and achieving high coverage in the face of data sparsity [33]. According to Sawar et al. [33], the amount of the amount of information is increasing far more than we can process it. Technology has drastically reduced the barriers used to publish and distribute information for a variety of purposes. As a result of the recent increase in information overload through technological advancements, researchers have in time realized the necessity, relevance and importance of creating technologies that can help users sift or filter through available information and find which is most valuable. Many of such technologies exist, namely, Collaborative Filtering (CF), Content-Based Filtering (CBF), Knowledge-Based, Utility-Based, Demographic and Context-Aware Recommender Systems. The most successful recommendation technique to date is Collaborative Filtering (CF). The basic ideas of CF algorithms are to provide item recommendations or predictions based on opinions of other like-minded users. The opinions of users can be obtained explicitly (recommender system allowing the user to provide relevant and necessary information needed for recommendation) or implicitly (the recommender system observing the behaviour e.g. purchasing behaviour and browsing habits of the user with the system and thus creating a user profile) [4, 34-42]. Collaborative filtering (CF) has been used successfully in various applications. For example, the Group-Lens system [43, 44] uses CF to recommend Usenet news and movies, and Amazon.com employs item-to-item CF to make recommendations based on the products that a customer has purchased and rated previously [45]. Collaborative Filtering (CF) Recommender Systems suffer from problems of *first rater (new item)*, *cold-start (new-user)*, *data sparsity*, and *scalability* [1-3, 33-45]. In contrast, content-based filtering derives recommendations by matching customer profiles with content features [1-4, 46]. In this category, recommendations are provided by automatically matching a user's interests with items' contents. Items that are similar

to ones the user preferred in the past are effectively recommended. It must be noted that recommendations are made without relying on information provided by other users, but solely on items', contents and users' profiles. In content-based filtering the features used to describe the content are of primary importance. The more descriptive they are the more accurate the prediction is. In Content-Based filtering only very similar items to previous items consumed by the user are recommended which creates a problem of *overspecialization* since there may be other items which are relevant and can be recommended but because they haven't been rated by the user before, recommendation becomes impossible [1-3, 33-40]. Several hybrid approaches combining collaborative and content-based methods have been proposed and outlined in [1-3, 33-40] which help to avoid certain limitations of content-based and collaborative methods. Different ways to combine both methods as well as other recommendation methods are investigated in Burke [36]. Recommender systems are established field of research and applications that have been and currently being studied well and extensively [47]. Major search engines like Google and electronic shops like Amazon have incorporated recommendation technology in their services in order to personalize their results [48]. Unfortunately, the algorithms underlying regular recommender systems are not directly transferable to the area of TEL. The TEL area offers some specific characteristics that are not met by today's general purpose recommendation approaches [1-4, 48]. The main difference is that each learner uses his/her own tools, methods, paths, collaborations and processes. Consequently, guidance within the learning process must be personalized to an extreme extent. For example, rather than recommending resources that other users with similar interests have used, the recommendation must also respect the actual learning situation of the learner, including the learning history, environment, timing and accessible resources [1-4, 48]. Furthermore, learning activities take place in learning environments that are composed of numerous tools and systems [1-4]. For instance, Learning Management Systems (LMSs) [49] as a notion of learning environments provide access to learning resources and collaboration facilities, but do not ensure that teachers or students of a course use them only [1-4, 48]. Normally and often times, learners use additional tools to collaborate or find resources - for example, in case that the learning material offered in the LMS is not sufficient [3]. Adaptive learning environments (ALEs) address these issues by providing support for personalized access to learning material [1-4, 26, 50]. Learning situations become even more multifarious due to the fact that pedagogical approaches differentiate between formal and informal learning processes [3, 4, 48]. Both have

different requirements for the learning environment and, as such, for the recommendation within the environment. Often, it is not possible to draw a clear line between formal and informal learning scenarios. For example, recommender systems need to deal with the tension of recommendations for activities liked by the learner and those required by the teacher as well as issues involving context such as location and time [1-4, 48]. Subsequently, there is the need and necessity for substantial amounts of data about the user and his/her activities within all of his/her learning environments, in order to facilitate precise recommendations. This leads to the problem of usage data availability [1-4, 48]. According to [1] TEL, this situation often does not occur. Instead, many learning activities take place with only a few learners participating.

D. Exploring Learner's Framework in Technology Enhanced Learning (TEL)

It is not possible to simply adjust existing recommendation techniques for TEL. There are a number of specific demands created by the learning and academic context which needs to be taken into account [1-4, 48]. Learner models have been researched extensively in the educational adaptive hypermedia and the educational user modeling research areas [1-4, 48]. The results in [4] proved a conclusion that it is important to classify learners into specific domains in TEL context, contrast to the commercial field. In this section, we review and briefly describe the main learner characteristics that have been proposed by Brusilovsky and Millan [51], Specht [52], Ling-Hsiu [53], Klačnja-Milicevic et al. [54] and Nguyen and Do [55].

1. Basic Personal Information of Learners

Basic personal information of learners in TEL typically includes identification information, name, contact information, affiliations, authentication information, information on accessibility, including language capabilities and disabilities, and other personal characteristics such as gender, age, profession and educational level [1-4, 48].

2. Learner Interests and Intentions

Learner interests capture interests or preferences of learners and are key characteristics to support personalization [1-4, 48, 54]. Values that are typically stored include search terms of the user, his/her tags, comments and resources he/she created, read or rated [3].

Traditional recommendation techniques use item-to-item similarity or user-to-user similarity to predict which products the user may be like, but do not take the specific domain user may be interested into account [1-4, 48]. This approach is reasonable, for consumers because for example men may buy clothing, electrical appliances, CDs, and

other items from any category. But this rule is not applicable in TEL context, because learners are interested in only a few areas such as his professional field [1-4, 48].

3. Learning Goals and Learner Social Network

The discrepancy of learning goals is often made between short-term goals, where a learner intends to solve a certain problem, and long-term goals that are related to a course or plans for life-long learning. Goal hierarchies that have been proposed decompose higher level goals in sub goals [51]. The social network of learner is also very important for TEL [4]. For instance two students whose major are computer science may both interest in Artificial Intelligence (AI) in academic context but have totally different preferences and interests in music. Therefore, it is necessary to take into account learners' academic social network in TEL in order to provide high quality recommendation services [1-4, 48, 51-55].

4. Knowledge/Performance of Learners and Learning Styles

The knowledge category represents prior knowledge levels of the learner [51]. Other researchers categorize this information under a performance nominator that stores information about measured performance of a learner through learning materials [56].

Different learners have different needs, preferences and approaches to learn [1-4, 48, 51-55]. For instance, some learners remember better when they see figures, tables, pictures, diagrams, charts, and demonstrations, but others learn more from words [3, 4]. Some learners understand information better by doing something actively such as discussing or applying it, but others tend to collect and analyze data before taking an action [1-4]. Psychologists call these individual differences as learning styles. The formal definition of learning style is that individuals differ in regard to what mode of instruction or study is the most effective for them [57].

The knowledge of learning styles can be utilized in many ways to enhance lifelong learning. A learning activity provider can be beneficial by getting information about how learners are used to learning, which provides them with a deeper understanding and might help them with recommendations of learning materials and resources [1-4]. Therefore, it is necessary to take learning style of learners and learning activities as an important factor in TEL recommendations [1-4].

5. Learner Cognitive Abilities and Styles

Existing recommender systems such as amazon and YouTube are entirely based on the

interests and tastes of the user. But users' cognitive abilities must be take account into in TEL. Even if learners' interests are the same for a particular domain, recommender systems in TEL need to recommend different learning activities depending on the individual proficiency levels [3, 4, 51-55]. For instance, the learners with no prior knowledge in a specific domain should be advised to study basic learning contents first, while more advanced learners should be advised to continue with more high-level learning contents [3, 4, 51-55].

Learners differ in their preferred way of learning presentation and cognitive processing. Examples for considering different cognitive styles are visual, textual, or auditory presentation of information. Different learning styles include the presentation of examples, presentation of theoretical knowledge, and practical exercises [3, 58]. Among others, researchers in TEL often refer to the Honey and Mumford [59] and Felder & Silverman [60] that describe an inventory of learning styles along several dimensions [3]. An interesting analysis of learning style classifications has been presented in Karagiannidis and Sampson [61].

V. RECOMMENDER SYSTEMS IN TECHNOLOGY ENHANCED LEARNING (TEL)

Recommender systems in TEL are quite diverse [3]. A recent survey of recommender systems in TEL has been presented by Manouselis et al. [1]. Most systems in [1] suggest learning resources [62] and/or people [63][64] who can help with a learning activity. Course recommenders [65] typically provide advice to learners on courses to enroll in. Several social navigation systems including [66] rely on recommendation techniques to suggest resource sequences.

A lot of research work [53][54] has been done in the E-learning Personalization field. These techniques mainly focus on Intelligent Tutoring Systems (ITS) [69]. Most current recommendation techniques that have been used in e-learning were established in the same way as in e-commerce without taking into account the pedagogic theory [1-4]. Some research projects in this area are based on different kinds of collaborative filtering methods, such as the I-Help system [67], and context e-learning with broadband techniques [68]. The authors in [11] realized the specific characteristics of Recommendation in TEL, but unfortunately the model they explored are still following the tradition ways such as collaborative filtering, without introduction of pedagogic factors [4]. Although existing recommendation techniques have been successful in e-commerce, making recommendations to learners is different from making recommendations in commercial fields [1-4, 48, 51-55].

Intelligent Tutoring Systems (ITSs) [69] which are not traditionally considered as recommender systems, use information about the learner to suggest personalized hints while he/she is solving a problem [3, 4]. Recommender systems usually rely on collaborative filtering, content-based filtering, knowledge-based filtering, context-aware filtering or hybrid recommendation algorithms [33-48]. A discussion of the advantages and drawbacks of the various techniques for TEL have been presented in [34-36]. These algorithms use information about users and resources to generate recommendations. Interestingly, most TEL recommender systems rely on profiles of learners or teachers that describe additional information as opposed to interests or preferences only [1- 4, 48, 51-55]. As we described above, the knowledge level of the learner is often used to personalize recommendations, such as his/her knowledge of course concepts or past academic grades [1-4, 48, 51-55]. Learning styles are also considered by some recommender systems in TEL [70][71], often based on the Felder and Silverman [60] inventory.

In [4] a discussion is presented on the way Lifelong Learning is a matter to knowledge society and Academic Recommendation is necessary to feed learners with the relevant and personalized contents. E-commerce recommendation system has made great success in book suggestion through Amazon. But these techniques are still not adapted to academic domain. The study in [4] found 4 factors, including learner's academic intention, social network, learning style and cognitive ability, which impact the effectiveness of Academic Recommendation systems. The study in [4] proposes a framework and model to build an Academic Recommendation system. A working system based on the novel model was constructed. The proposed system in [4] has explored 1099793 webpages, 34737 videos, 910 experts, 13416 courses, 47390 publications, providing search, profiling, and suggestions functionality for 100,000 users.

Personal learning environments (PLEs) aim at putting the learner central stage and comprise a technological approach towards learning tools, services, and artifacts gathered from various usage contexts and to be used by learners. Due to the varying technical skills and competences of PLE users, recommendations appear to be useful for empowering learners to set up their environments so that they can connect to learner networks and collaborate on shared artifacts by using the tools available. In [72] an examination is conducted using different recommender strategies on their applicability in PLE settings. After reviewing different techniques given by literature and experimenting with a prototypic PLE solution, the

study in [72] came to the conclusion to start with an item-based strategy and extend it with model-based and iterative techniques for generating recommendations for PLEs.

The study in [73] proposed a system based on hypothesis that involved asking for help from others: 1) the closer people are, the easier it is to get help, 2) the more simple things are, the more it is easier to get help with them. The study in [73] carried out a survey to examine the above hypothesis. The results in [73] showed that these hypotheses are correct. Based on these hypotheses, the study in [73] proposed a social networking service site based on a mobile environment called SENSIMILE, which supports learners to find a partner who can solve their problems at the online community, and an appropriate request chain of friends will be recommended upon their request by utilizing personal relationships. The system also supports collaborative learning by using location-based sensing information.

The study in [74] presented a solution for recommending documents to students according to their current activity that is tracked in terms of semantic annotations associated to the accessed resources. The approach used in [74] is based on an existing tracking system that captures the user current activity, which is extended to build a user profile that comprises his/her interests in term of ontological concepts. A recommendation service is elaborated, implementing an algorithm that is alimented by Contextualized Attention Metadata (CAM) comprising the annotation of documents accessed by learners. The user profile is updated as soon as an activity is completed; thus, recommendations provided by the service are up-to-date in real time. The original aspect of the recommendation approach in [74] consists of combining a user activity tracking system with the exploitation of the semantic annotations associated with resources.

According to studies into learning at work, interpersonal help seeking is the most important strategy of how people acquire knowledge at their workplaces. Finding knowledgeable persons, however, can often be difficult for several reasons. Expert finding systems can support the process of identifying knowledgeable colleagues thus facilitating communication and collaboration within an organization. In order to provide the expert finding functionality, an underlying user model is needed that represents the characteristics of each individual user. The study in [75] discusses requirements for user models for the Work Integrated Learning (WIL) situation. The study in [75] presents the APOSDLE People Recommender Service which is based on an underlying domain

model, and on the APOSDLE User Model. The study in [75] describes the APOSDLE People Recommender Service on the basis of the Intuitive Domain Model of expert finding systems, and explains how this service can support interpersonal help seeking at workplaces.

VI. DISCUSSION AND OPEN ISSUES

Existing recommendation techniques cannot be applied directly in TEL due to the differences between academic and traditional commercial context [1-4]. Existing work in recommender systems [33-46, 66, 76] identifies a subtle difference between various parameters of contextual information in TEL. Existing work in recommender systems refer to multi-dimensional spaces for representing contextual variables, and identify mainly three categories/dimensions within which variables may be grouped (i.e. user, item, context and content) [3]. However, in terms of research and development, there is a challenge of reaching towards an identification of these variables, as well as their grouping in categories [1-4, 51-55].

For example, one could argue that physical conditions are part of location variables, or at least strongly linked to them. Or that learner models are actually user models that are not related to the context [3]. To this end, reaching a generalization that will incorporate all single or multidimensional representations in a single model can be considered unrealistic [3]. A possible line of future work and an open issue of recommender systems in TEL is mapping/linking the various representations of TEL in recommender systems, so that contextual data may be exchanged among different systems [3, 4]. In addition, other open research issues could involve the extension of the recommender strategy through hybrid approaches such as multi-attribute and clustering techniques as well as model-based generation of recommendations with an evaluation strategy [1-4].

VII. CONCLUSION

The proliferation of Information and Communication Technology (ICT) coupled with the Internet has paved way for an enormous amount of information overload for users that seek information in a variety of disciplines including education, academia and TEL. This paper reviewed recommender systems in TEL with a focus on users (learners) framework within existing research. This review paper ascertained that recommender systems applied in commercial context cannot be directly applied in TEL due to the sensitive nature of interests and preferences of learners in the academic context. Results of the review indicate that there has been much advancement in the development of TEL recommenders in recent years by many researchers. Many promising prototypes illustrate the potential

and opportunities that are created in TEL recommender systems.

However, important challenges related to the capturing and use of contextual data need to be tackled in order to increase uptake and validate research efforts in realistic trial experiments.

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