Journal of Web Engineering, Vol. 17, No.3&4 (2018) 284-304

IMPLEMENTATION AND EVALUATION OF A RESOURCE-BASED LEARNING RECOMMENDER BASED ON LEARNING STYLE AND WEB PAGE FEATURES

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Received October 15, 2016
Revised June 3, 2018

It is generally believed that recommender systems are a suitable key to overcome the information overload problem. In recent years, a special research area in this domain has emerged that concerns recommender systems for Technology Enhanced Learning, in particular, self-regulated learning with resources on the web, known as Resource-Based Learning. Grey-sheep users are a major challenge in RecsysTEL. This group of users have completely different opinions from other users. They do not profit from collaborative algorithms, so they must be supported in discovering learning resources relevant to their characteristics and needs. The main contribution of this work is to develop a feature-based educational recommender system which interacts with the user based on his or her learning style. The learning style dimensions would be determined based on Felder-Silverman theory. In addition, the system crawls and extracts the necessary meta-data of sample OCW's web pages. Based on the proposed web page ranking formula, the user's learning style dimension and web page feature's vector would be accommodated to generate learning object suggestions. The general satisfaction, perception and motivation towards the proposed method measured among 77 science and engineering students by a questionnaire. Moreover, the system has been evaluated to provide feedbacks on its suitability. The research findings imply that the proposed method outperforms the general search algorithm. This system can be used as a template in formal and informal learning and educational environments as a RecsysTEL.

Key words: Educational recommender systems, Technology Enhanced Learning, Resource-based learning, Index of Learning Styles, Recommender Systems for TEL, Web page attributes, Web page ranking
Communicated by: B.White & C. Bieber

1 Introduction

Improvement of all forms of learning practices, for people and organizations, is the main objective of Technology-Enhanced Learning (TEL). As an application domain, it includes all kinds of technology research and development aiming to support training activities and learning process [1, 2]. With the high rate of web growth, users are faced with an overload of information. Moreover, resource-based learning is a form of self-regulated training. An open-ended challenge in TEL supports learners in finding learning resources relevant to their current needs and learning goals. Any recommendation technologies in this regard must ease the access to educational resources. Recommender systems are designed to overcome the information overloading problem using large amounts of the existing users and online resources. They form a broad recognized and well-established arena of research and applications [3]. The recommender systems have been reviewed greatly in several surveys of the state-of-the-art [4, 5]. The first efforts to study and work on topics related to recommender systems for TEL were made in workshops in 2007 [1]. Recommenders have a significant role in identifying and deriving relevant information and appropriate materials to learners, from a potentially wide variety of choices buried in a large amount of unrelated resources [6]. Obviously, there are some features to consider in learning applications that must be differentiated from non-educational systems. The recommendation system for TEL or RecsysTEL [7] offers some specific characteristics that are not met by the general-purpose recommendation approaches. Therefore, their algorithms are not directly applicable [8]. The learner often uses his or her own tools, methods and processes. RecsysTEL must support learners by providing them with related educational resources and predicting their requirements with respect to their traits, behavior, profiles, history logs and pedagogical aspects [9]. In this context, an intelligent agent suggests sophisticated recommendations based on the user's previous actions, profile and characteristics. Most recommenders suffer from two well-known problems: cold start [10] and sparsity [4]. However, in RecsysTEL, there is another problem named grey-sheep users [11]. It corresponds to users that have little similarity with their peers. The grey-sheep user has special preferences (i.e. preferring or favoring one thing over another) that do not consistently agree or disagree with any community of users. So, a collaborative-filtering recommender does not provide them with high quality and suitable recommendations.

The major goal of this research is to overcome the above-mentioned challenge and to improve the suitability of recommending learning objects. On this basis, an educational recommender system has been developed to investigate the possibility of accommodating the computed user's learning style and web page features in order to deliver the best educational resources to every user. The paper is organized as follows: first, the concept of 'adaptive hypermedia systems' is discussed. Then, in section 3, recommender systems are concisely reviewed. Also, the particularities of the TEL application domain in this field are discussed in section 4. After, the concept of 'user modeling' is introduced in section 5. The learning style theory and, in particular, Felder-Silverman dimensions are explained briefly in section 6. Next, our proposed approach and the web page ranking formula are presented in section 7. The user's feedback is analytically evaluated in detail in section 8. It includes the evaluation part of the results that has been comprehensively discussed. Finally, a conclusion paragraph closes up the paper.

2 Adaptive Educational Hypermedia system

There are many diverse needs of users in the web which must be fulfilled. Adaptive web systems, or *adaptive hypermedia,* serve to make this fulfillment. Hypermedia is an extension of the term 'hypertext'. It is a combination of 'hypertext' and 'multimedia'. Obviously, the web is a universe of interacting hypermedia documents. Hypermedia allows links to be embedded in multimedia elements such as images, graphics, movies, music and videos. It is a complex module of a software, consisting of several parts which serve the user an associative, point-and-click interface to a set of documents [12]. In other words, an adaptive system adjusts itself to various circumstances. The user's interest, goals, tasks and preferences are used in the process of adaptation. User's properties are stored in a profile or in a user model. The system constructs the user model and stores his or her detailed preferences. Studies on Adaptive Hypermedia Systems started around 1990 [13]. Nowadays, many sites and industries use different kinds of adaptive systems. Peter Brusilovsky presented an overview of adaptive hypermedia systems in 1996 [14]. As he noted, "*By adaptive hypermedia systems we mean all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible aspects of the system to the user. In other words, the system should satisfy three criteria: it should be a hypertext or hypermedia system; it should have a user model; it should be able to adapt the hypermedia using this model*" [15]. It is generally accepted that applying hypertext and hypermedia in any situation is beneficial, especially in *Adaptive Educational Hypermedia* Systems (AEHS) [16]. As its name suggests, AEHS is applied in the process of training. In e-learning environments, it enables students to use customized educational contents. There are different research fields that are assigned to the development of AEH systems such as educational technology, intelligent tutoring systems, cognitive science and computer engineering. In e-learning and intelligent tutoring systems, AEH is developed to overcome the weak points of traditional *one-size-fits-all* problem [1]. Besides, its application is not limited to formal and informal education environments. According to Henze and Nejdl [17], a document space, a user model, observations and an adaptation component are four components of an AEH system. The first element will be stablished based on the hypermedia system (e.g. notes, domain or knowledge graphs). The second component collects, defines and concludes knowledge and preferences about the user. The interactions between the user and the system are recognized by observations, that are used to update the user model [18]. Hence, a general model for an adaptive educational system has four essential modules as follows:

1- Domain Model, or a set of domain concepts each of which has some topics of knowledge. The structure of the knowledge domain is based on the semantic network of the topics that are linked to one another.

2- Student Model, or a student's personal, cognitive knowledge profile, that precisely reveals the characteristics of different users [19, 20].

3- Content Model, or educational contents in terms of the Domain Model concepts. In its simple form, it links every content item to just one domain concept [20].

4- Adaptation Module, or a user interface that shows information to the user based on his or her cognitive preferences [19].

In [21] several kinds of adaptive learning have been discussed. In the following section, one of the most important applications of this system, namely recommender systems, will be introduced.

3 Recommender systems

Overloaded information is the result of penetrating of the web increasingly. It makes it difficult for the user to gain access to the desire information. Search engines solve this problem, to some extent. However, they do not provide the personalization of data. A recommender engine has an essential role in overcoming this challenge by helping users find desired information [22]. It help users make decisions in this perplexed information space where a large amount of information is available to them [23]. Moreover, they are a category of information filtering system that aims its user on predicting the 'preference' or 'rating' given to an item. Tintarev and Masthoff presented seven advantages of using recommender systems [24]. Equipping users with proper recommendations to satisfy them is of the highest importance. Recommender systems became an independent research area in the mid-1990s [2] with works on the rating methods. Recently, a number of recommender systems have been broadly developed in a variety of domains and applications such as movies, news and e-learning [25]. Especially, they have been researched extensively by the Technology Enhanced Learning (TEL) area. In this domain, the suitable resources from a pool of learning objects are identified. The recommenders anticipate and offer different facilities such as a promising approach to make both learning and training tasks fluent and to increase the diversity of recommendation lists. Recommendations improve learners' learning path. In the learning process, the search engines often have a low precision. Implementation of these systems requires some interdisciplinary work. It involves experts from various fields such as Information Technology (IT), Artificial Intelligence (AI), Data Mining, Human Computer Interaction (HCI), User Interfaces, Consumer Behavior, Decision Support Systems (DSS) and Statistics [2]. Recommendation systems can be categorized based on their forms of intercommunication with the user, source data and ways of adjusting their knowledge. In other words, they can be roughly classified into several categories. It depends on the information that they use to recommend items. Several recommendation algorithms, such as content-based filtering [26-28], collaborative filtering [29, 30] and their hybridizations [31, 32], are widely discussed in several surveys of the state-of-the-art [4]. The content-based algorithm recommends items similar to the ones that user preferred in the past. It uses the information of active users and the data about the items. On the other hand, collaborative filtering-based methods predict user interests directly from his or her peers with similar interests and preferences in the past [29]. In other words, it uses information of users and their relations with the item to offer recommendations to the active user. NEWER is a sample of an online recommendation system based on collaborative filtering [33]. Hybrid methods use a combination of these two methods to improve recommender performance [5, 32]. They seek to overcome the limitations of the other approaches. A comprehensive discussion of the advantages and disadvantages of these techniques for TEL is presented in [1]. The authors made a broad survey of TEL recommender systems. Recommender systems are greatly domain-dependent [34]. So, their methods and requirements cannot be usually applied directly in educational recommenders [35].

In the next section, the particularities of TEL domain will be discussed for recommendations as well as the present study.

4 Particularities of TEL for recommendation (RecsysTEL)

Recently, most search engines and e-commerce web sites have included recommendation expertise in their services to personalize their outputs. It is noticeable that the general-purpose methods implemented in these regular recommender systems and the information retrieval goals of them are not directly applicable to the domain of TEL [8, 35]. Learning is a process and a continuous effort that regularly takes more time and interactions compared to a commercial transaction. So it is necessary to separate the particularities of TEL recommender systems. It is used to sophisticate the methods that improve efficient design, development and evaluation of these systems. Learning is also a complicated process that often needs more time and interactions than a commercial transaction. So, the learners seldom reach the end-state after a limited time. Learning activities take place in special personalized environments that are composed of different tools and utilities. For example, in a learning management system (LMS) [36] ease and facility to access the learning resources and collaboration benefits is desirable. Tracing the learner's progress and activities is a necessity in such environments. However, it does not guarantee that learners will exclusively use them. Rather, they may use additional tools to find their resources. Applying pedagogical aspects is another consideration that makes learning situations more complicated [37]. This is why using the recommender systems in TEL makes its application quite different. As mentioned before, a recent comprehensive survey of this application has been presented by Manouselis *et al.* [1]. Learning resources are suggested by most recent systems [38]. Normally, course recommenders [39] provide suggestions and advice to learners on appropriate course resources. In this situation, most RecsysTELs deal with the learners' profiles. To personalize the recommendations, some user's characteristics, such as the knowledge level and learning style of the learner, often based on the Felder-Silverman [40] theory, are used. On the other hand, to increase the accuracy, some systems use resource features such as multimedia facilities, audio, video, graph and charts. These features describe the multiple attributes of the resources. Many systems, in addition to the general characteristics of resources like author, title, published date and keywords, use other educational metadata to categorize the difficulty level of a resource.

In the next section, the user modeling, as an important component of such systems, will be discussed.

5 User modeling

Generally, building the information repository of objectives, preferences and knowledge of each user is referred to as 'user modeling'. A user model is a representation of the user's information, knowledge, interests and preferences [41]. Also, it prepares the knowledge about the user's characteristics, allowing the system to express, conclude and extract the required assumptions and information. One distinct section of an adaptive educational system [42] is a user model [43, 44]. Generally, Adaptive Hypermedia is mentioned as a crossroad in the research of Hypermedia and User Modeling. It is accepted that user modeling plays a main role in the success of recommender systems [45]. Usually, user modeling refers to the works of Allen, Cohen, Perrault, and Elaine Rich [46]. In the context of applications, a user model must represent the needed characteristics of the user. Koch describes the application of user models as follows: "*Users are different: they have different background, different knowledge about a subject, different preferences, goals, and interests. To individualize, personalize or customize actions a user model is needed that allows for selection of individualized responses to the user*" [41]. So, if a personalized output of a system is expected, a user model should be used. User model is useful for different types of systems, such as recommenders. It may be expected that a user model includes only attributes of a user (e.g. preferences, domain knowledge, goals, etc.). In the meanwhile, it just stores limitations of the user's perception (e.g. his or her disabilities). If these limitations are considered, the most adaptation occur [41]. Usually, the terms user modeling and user profiling are used as interchangeable synonyms. Koch defines a user profile as a simple user model [47]. A user profile is a set of personal information stored without adding further description or inferring. It consists of cognitive skills, intellectual abilities and intentions, learning style dimensions and a log of preferences and interactions with the system. After their values are assigned, these properties are saved. They usually change over time [44, 48], but some features may be final. The user's model will be constructed based on the collected user's data. Therefore, the user profile is used to conclude the information needed to construct a user model. These concepts can, thus, have distinct functions and meanings. In this research, the generic data, such as name, surname, email, password, gender, demographic data, academics background and cognitive data including learning style are collected to build a user's profile.

It is generally accepted that the manner in which a learner chooses in a learning situation has an impact on performance and achievement of the learning outcomes. So, Learning Style is a learning-related concept which, particularly gives some valuable insights into learning. A corresponding concept is presented in the next section.

6 Learning style theory

Learners with dissimilar experiences and backgrounds have different preferences of learning. Also, teaching methods vary. Over the past decades, a wide diversity of theories and models concerning learning styles have been presented [49]. The terms *learning style* and *cognitive style* are usually used in research texts interchangeably. The learning-style concept was used firstly by R. Dunn in 1960 [50]. It has been defined as unique manners in which individuals begin to focus, process, act, and by which they keep in mind new and hard information [51]. The cognitive style, however, was defined by Allport in 1973, as a personal regular or routine manner of remembering, thinking, problem solving and feeling [52]. Therefore, the cognitive style is regarded as a main component of learning style. It is generally accepted that everyone learns in a different way. That is, everyone has a different and specific learning style. It means that anybody obtains and deduces data through a different intellectual filters [53]. Learning style is the manner in which a person recognizes and shapes information [54]. It defines learner's preferences for different kinds of learning and teaching activities [55]. Also, it is a particular way of gaining knowledge from practical challenges of the learning environment [56]. Therefore, it has an effect on the quality of learning results [57]. Identifying the learner's learning style is the best way to get information about his or her habits and manner of learning. So, applying this information in any e-learning system can have an improving effect on the training quality [50]. In addition, different students select different strategies to deal with their tasks. Some learn by texts, while others prefer graphs and images. Other learners study independently, while others work in a team. These preferred situations have been characterized and modeled. In 1988, Richard Felder and Linda Silverman, developed one of the most widely used models (known as FSLSM or Felder and Silverman Learning Style Model) in the Index of Learning Styles (ILS) psychometric instrument [58] for basic (at least below the graduate school level) sciences and engineering students. ILS is a self-scoring web-based instrument that assesses preferences on the Felder-Silverman dimensions proposing a list of items effective in identifying the style of each learner. It is available free to web users who wish to use it for teaching or research in a formal teaching situation. Also, it is licensed to companies and individuals who plan to use it for broader research works or for services given to customers or clients. ILS and its information are available at [59]. Table 1 shows the questions of its dimensions [60]. The comprehensive definition of these dimensions can be studied from the original work by Felder and Silverman.

Style	Semantic Groups	ILS Questions	Style	Semantic Groups	ILS Questions
Active	trying something out	1, 17, 25, 29	Reflective	think about material	1, 5, 17, 25, 29
	social oriented	5, 9, 13, 21, 33, 37, 41		impersonal oriented	9, 13, 21, 33, 37, 41
Sensing	existing ways	2, 30, 34	Intuitive	new ways	2, 14, 22, 26, 30, 34
	concrete material	6, 10, 14, 18, 26, 38		abstract material	6, 10, 18, 38
	careful with details	22, 42		not careful with details	42
Visual	pictures	3, 7, 11, 15, 19, 23, 27, 31, 35, 39, 43	Verbal	spoken words	3, 7, 15, 19, 27, 35
				written words	3, 7, 11, 23, 31, 39
				difficulty with visual style	43
Sequential	detail oriented	4, 28, 40	Global	overall picture	4, 8, 12, 16, 28, 40
	sequential progress	20, 24, 32, 36, 44		non-sequential progress	24, 32
	from parts to the whole	8, 12, 16		relations/connections	20, 36, 44

Table 1- Semantic groups associated with the ILS questions of Felder and Solomon

FSLSM divides users more accurately than other models and has the best dimensions for personalization. It combines some major learning style models [40, 50, 61]. The distribution of learning styles theories implemented in adaptive learning systems indicates that this approach is popular and more used in research papers [62] (Figure 1).

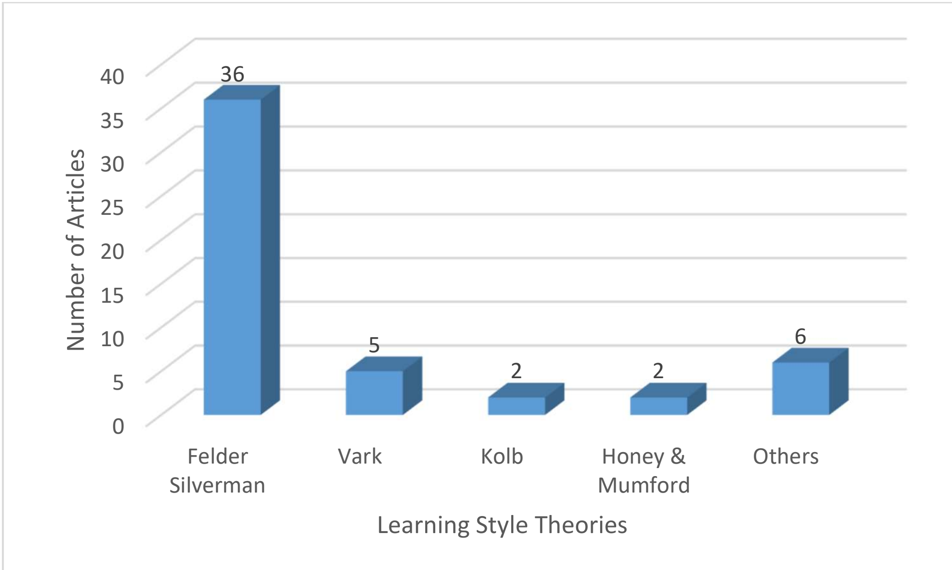


Figure 1 Learning styles theories applied in adaptive learning system [62].

The first published Felder's model consisted of five different dimensions including Active-Reflective, Global-Sequential, Inductive-Deductive, Sensitive-Intuitive and Visual-Auditory. However, he decided to drop the Inductive-Deductive dimension. Also he changed the Auditory to verbal. In [40], he has explained the reasons for these changes. Therefore, FSLMS has four dimensions that measures the learners' favorites in the learning style model. Active learners learn by trying and doing physical experiments, self-assessment exercises and multiple questions. They enjoy working with others and prefer discussing, explaining and testing the information in a group. In contrast, reflective ones learn by thinking deeply and working in isolation. They evaluate options, learn by analysis, enjoy studying a problem on their own and deal with examples, outlines, summaries and result pages. Sensing learners like to learn detailed materials and tend to be practical. They like observing, gathering data through the senses, and seeking the facts. They also prefer practical and concrete, examples, explanation, facts and procedural information. Intuitive learners, on the other hand, prefer to learn abstract subjects such as theories, definitions, algorithms and their meanings and tend to be more innovative than sensing ones. Visual learners remember best what they have seen. Therefore, these learners prefer resources with visual representation such as graphs, pictures, diagrams, charts, videos, animations and schematics. On the other hand, verbal learners like written or spoken explanations with words like those in texts or audio materials; thus, they prefer to read or hear information. Sequential learners learn in a step-by-step manner and prefer to have information presented in an orderly approach and a linear way such as doing one-by-one exercises and constricting link pages. In contrast, global learners prefer outlines, summaries, all-link pages and a holistic and systematic approach. They learn in large leaps and see the big picture first, then the details [63].

Identification and understanding of a learner's preferences and FLSM's dimensions [64, 65] will be taken into account in the proposed resource-based recommender to choose and rank an appropriate web page. Most learning style dimensions parallel one another [40]. The quality of learning of active learners when working in a group is not comparable to that when working in passive situations. While, the reflective learners solve a problem more effectively, when they think about it on their own. In the next section the proposed idea has been described.

7 The proposed approach

Recommender systems are believed to have several shortcomings. In most papers, sparsity and cold-start have been referred to as the general problems of those systems. The small number of item ratings has led to their sparsity [4]. Also, lack of knowledge about a new user's choices, preferences and favorites has led to their cold-start [10]. In RecsysTEL domain, there exists another problem. The results of collaborative algorithms are not useful for some users with opinions regularly different from the group opinions. This is known as the 'grey-sheep problem' [29, 66]. To overcome this problem and to improve the accuracy and efficiency of recommendations, this paper proposes a formal approach in which each educational web page for every user is ranked based on his or her learning style. As mentioned before, everyone inclines to learn in a diverse and distinct style [50]. Generally, questionnaire and log file analysis, are the two popular approaches by which to mine learners' styles. Regarding the first approach, Felder and Solomon developed a questionnaire with 44 items which completely covers the Felder and Silverman theory on learning style [67]. As the first step, based on the Felder-Silverman learning styles model, a web site was developed to gather the data of the ILS questionnaire taken from different students of Yazd universities, Iran, during two semesters. The extracted and computed learning style dimensions served as the decision-making parameters for proposing appropriate pages. The system extracts the results based on research carried out by Litzinger [67]. At the next step, in order to collect the resources, relevant to the user search query, a web crawler [68, 69] was developed. A web crawler is a program that, once given one or more seed URLs, downloads the web pages associated with these URLs, extracts any hyperlinks contained, and recursively continues to download the web pages identified by these hyperlinks. Designing of a high-performance web crawler is a challenging task [70]. In this regard, an interesting technique is focused crawling [71]. It concerns the development of particular crawlers able to seek out and collect subsets of web pages that satisfy some specific requirements. In particular, if the goal is to collect pages related to a given topic chosen by the user, the crawlers are usually named focused or topical. Focused crawlers are also employed in different domains from specialized IR-based [72] search engines but they are usually related to the retrieval and monitoring of useful hyper-textual information. In this research, educational web pages, especially the Open Courseware Consortium [73] (OCW sites), were selected as the recommender resource. Figure 2 shows the process of feature page modeling of a web page.

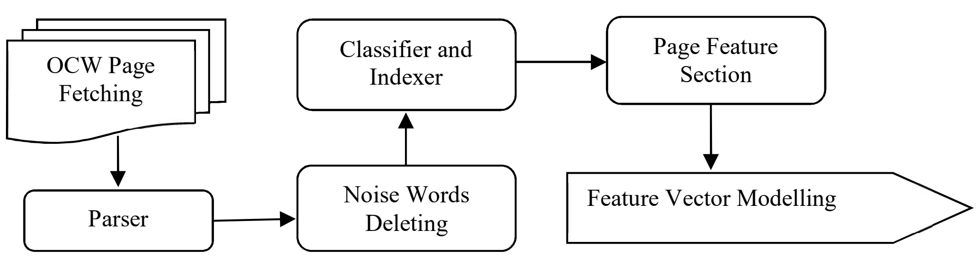


Figure 2 Educational Resource Extraction Process.

		Learning Style Dimensions							
		Input		Perception		Process		Understanding	
		Verbal	Visual	Intuitive	Sensing	Active	Reflective	Global	Sequential
Educational Page Features	Challenging and Discussion	1	0.5	1	0.5	1	0.5	0	0
	Exercise	1	0.5	1	0.5	1	0.5	0	0.5
	Graph, Image, Diagram and Video	0	1	0.5	1	0	0.5	1	0.5
	Audio and Lecture	1	0	0.5	0	0	1	0.5	0
	Observation and Experiment	0	1	0.5	1	1	0.5	0	0.5
	Outline	0.5	0	0	0	0	0	1	0.5
	Questionnaire and Self-assessment exercise and test	0	0	0	0	0.5	0	0	0.5
	Simulation	0	1	0	1	1	0	0.5	0
	Slide	0.5	1	0.5	0.5	0	0.5	1	0.5
	Table	0.5	1	0	0.5	0	0	0.5	0.5
	Text and Reading	1	0	0.5	0	0.5	1	0.5	1

Table 2- Relation between Learning Styles Dimensions and Resource Learning Pages

To select the appropriate pages, some features were determined. The domain area subject of user demand keyword, multimedia facilities, course authority, page visit rate, exercises, update rate and freshness, test and quiz, video, text, diagram, and image are some of the parameters considered for recommendations. At the next step, these features had to be adapted and accommodated to user's style dimension. For example, for a visual learner, the best page to recommend would be the one including videos and diagrams and the worst case would be text pages. So, some features will be extracted from each page, which are referred to as *General Page Feature* (*GPF*). *Page Publisher and Title, Primary* *and Subsidiary Subject, Course Educational Level* (Graduate, Undergraduate, etc.)*, Visit Rate, Publish Date, Weighted In-Link* from other sites*, Popularity of Page* computed by *Alexa* [74] *Ranking, the Number of Pages* on the website, and some Demographic Info (such as words count) are some instances of GPFs. Then, a subset of these features was selected to accommodate. They are named *Educational Page Feature* (EPF). According to Learning Styles and Strategies defined by Richard Felder and Barbara Soloman, an adaptation scale has been assigned between the EPFs and each of the learning style dimensions. This scale is named *Goodness Factor* (GF). The proposed GF's are indicated in Table 2 [63].

They have been extracted according to [53, 58, 67, 75-79]. As an illustration, number zero indicates that the relative EPF is ineffective for the corresponding learning style dimension. Whereas, number 1 shows the maximum effectiveness of that feature, and finally, number 0.5 demonstrates that the effectiveness of the corresponding feature is nearly medium. For example, the "Graph, Image, Diagram and Video" EPF has a GF of 0 for a verbal person whereas it has a GF 1 for a visual person. Then page rank of page P_j for user U_i is computed based on equation (1) [63]:

$$UPR(U_i.P_j) = \sum_{k=1}^{8} D_{k_{U_i}} \times \left(\sum_{l=1}^{EPF_s\ no} \left[EPFS(P_j.EPF_l) \times GF(EPF_l.D_k)\right]\right) \quad Equation(1)$$

$$UPS(U_i.P_j) = \mathrm{F}(UPR(U_i.P_j).GPR(P_j))$$

Where:

1	$UPR(U_i.P_j)$:	Computes ranking of page P_j for user U_i
2	$D_{k_{U_i}}$:	is the computed corresponding learning style dimension score for user U_i (e.g. $D_{1_{U_i}}$= 0.7 shows that user U_i has a score of 0.7 in the verbal style dimension or s/he is a 70% verbal person)
3	$EPFS(P_j.EPF_l)$:	Shows what percentage of page P_j includes feature EPF_l (e.g. $EPFS(P_j.EPF_2)$= 0.7 shows that 70% of page P_j includes Exercises)
4	$GF(EPF_l.D_k)$:	is the Goodness Factor of feature EPF_l against learning style dimension of D_k (extracted from the numbers of Table 2)
5	$GPR(P_j)$:	is a profile independent score for page P_j which is computed using a combinational function based on a query dependent score (such as TF-IDF [80], BM25 [81], …) and a query independent score (such as PageRank [82], DistanceRank [83], …)

6	$UPS(U_i.P_j)$:	computes the Score of Page P_j for User U_i. Note that the difference between UPS and UPR is that in UPS computation, the GPR of the page is also considered
7	F:	is an arbitrary function. The only limitation of the function is that it should be ascendant on each of its parameters (i.e. if $UPR(U_i.P_j)$ or $GPR(P_j)$ increases, $UPS(U_i.P_j)$ also raises)

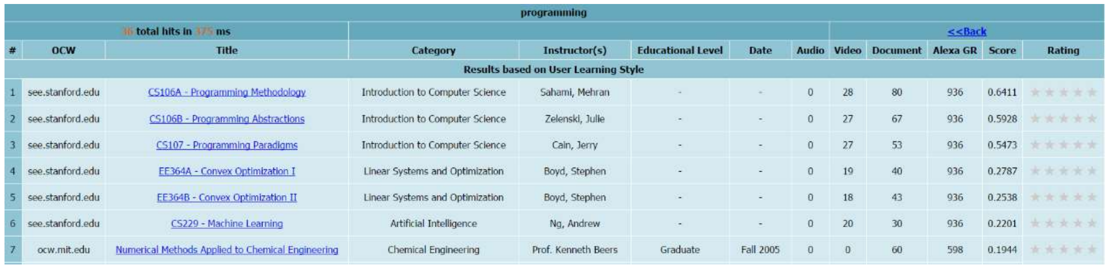
After the user's query was received in a search dialog, a subset of pages, available in the repository, are selected. This selection is based on the pages' content relevance score against the query. Then, Equation (1), would be applied to the pages to rank the results based on the user's style vector.

The system's user interface shows the results in two parts. The first part includes ten recommendations based on Equation (1). The second shows the results of web page rankings without considering the user's style dimension. It is based on Lucene algorithm. Accordingly, the user can compare results of the proposed method to a general web page ranking algorithm. The issue of the users' satisfaction is discussed in the next section.

8 Evaluation

The effectiveness of Equation (1) is studied in this section. Two separate web sites, for the purpose of modularity and independency, have been developed. The first is a web site to assess the user's learning style based on ILS [84]. The second is a web application resource-based recommender to suggest OCW's web pages independently. The research idea and the proposed page-ranking formula have been implemented on the second web site. Up to now, 370 academic users have worked with the learning style detection by the ILS approach web site and 77 participants with the resource-based recommender system. In [85], three different methods of evaluation have been investigated for RecsysTEL. They include measuring (i) the system performance, (ii) the learning effectiveness and (iii) the User-Centric effects. The first measurement includes the execution time or speed of a recommender algorithm in generating the recommendations. The second method of evaluation aims to measure the educational goals achievements. The third category discovers the general perception of the recommender system by the user.

For measuring the learning goal achievements, an e-learning environment was provided for a representative group of students at Yazd University, Iran, within two semesters. This platform was included in an LMS system called Samiad. A comparison of the results of a pre-test given at the beginning of the course and a post-test at the end of the course in each semester, showed that using this method has a considerable effect on students' learning goals. The grades show that there is a 30% average improvement from pre-test to post-test. The general perception of the recommender system confirms the effectiveness of our learning style-based algorithm. The proposed resource-based recommender, compared to a raw algorithm, using Apache Lucene [86]. Lucene is a widely used open source text-search library. It only incorporates the query-dependent score functions. In other words, it does not include the user's learning style preferences. Recommendations were delivered in two separate sections in a graphical user interface (Figure 3).



programming												
[illegible] total hits in [illegible] ms								<<Back				
#	OCW	Title	Category	Instructor(s)	Educational Level	Date	Audio	Video	Document	Alexa GR	Score	Rating
Results based on User Learning Style												
1	see.stanford.edu	CS106A - Programming Methodology	Introduction to Computer Science	Sahami, Mehran	-	-	0	28	80	936	0.6411	
2	see.stanford.edu	CS106B - Programming Abstractions	Introduction to Computer Science	Zelenski, Julie	-	-	0	27	67	936	0.5928	
3	see.stanford.edu	CS107 - Programming Paradigms	Introduction to Computer Science	Cain, Jerry	-	-	0	27	53	936	0.5473	
4	see.stanford.edu	EE364A - Convex Optimization I	Linear Systems and Optimization	Boyd, Stephen	-	-	0	19	40	936	0.2787	
5	see.stanford.edu	EE364B - Convex Optimization II	Linear Systems and Optimization	Boyd, Stephen	-	-	0	18	43	936	0.2538	
6	see.stanford.edu	CS229 - Machine Learning	Artificial Intelligence	Ng, Andrew	-	-	0	20	30	936	0.2201	
7	ocw.mit.edu	Numerical Methods Applied to Chemical Engineering	Chemical Engineering	Prof. Kenneth Beers	Graduate	Fall 2005	0	0	60	598	0.1944	

Figure 3 Graphical user interface of the proposed recommender system.

The user can see some GPF and EPF features. These meta-data help to decide on choosing an appropriate OCW. The suitability of every web page link that the system suggests, is evaluated by user opinion on a five-level rating scale (Figure 3). The system has been evaluated by a group of academic users for its accuracy. The results have been reported in another paper [63].

Question's Goals	Question
Recommendation Accuracy	The items recommended to me matched my interests.
Recommendation Novelty	The items recommended to me are novel.
Explanation	The recommender explains why the resources are recommended to me by their meta data.
Recommendation Diversity	The items recommended to me are diverse.
Recommendation Comprehensive	The recommender items cover the most my needs.
Recommendation Sufficiency	The information provided for the recommended items is sufficient for me to make a choice decision.
Interface Adequacy	The layout of the recommender interface is attractive, clear and adequate.
Interface Simplicity	The user interface is simple and adequate
Interactions Simplicity	The interactions with system (like select an item and feedback) is simple
Transparency	I understood why the items were recommended to me by the OCW's meta data.
Perceived Ease of navigation	The navigation between sections is easy.
Perceived Ease of Understand	I easily understand the view, interaction and meaning of recommended items.
Trust	I trust the system.
Suggest to Others	I will tell my friends about this recommender.
Using Intention	I use it again because the system uses my learning style dimensions to recommend the suitable item.
Related to learning goals	The recommender items are related to my learning goals and the help me to achieve them.
Confidence	Using the system rise my motivation and self-confidence in my learning goals
Self-Satisfaction	I find using the system attractive and self-motivated
Privacy Preservation	The system preserves my personal data.
Overall Satisfaction	Overall, I am satisfied with the recommender.

Table 3- The user questionnaire to evaluate the general perception of the proposed recommender system

Furthermore, to determine the overall satisfaction of the users with what they think and feel while using the recommender system, a questionnaire was designed based on [45, 87] (Table 3). A five-level Likert item is used for the questionnaire. It has "strongly disagree, disagree, neither agree nor disagree, agree, strongly agree" options for either positive or negative response to questions.

According to the theory of Planned Behavior [88], behavioral intention is a strong predictor of an actual behavior. The goals of each questions can be discussed in four general dimensions: user interface (i.e. adequacy, simplicity, perceived ease of navigation and understanding), impression of recommendations (i.e. accuracy, novelty, diversity, sufficiency of the user interface), system efficiency (i.e. trust, privacy preservation, perceived ease of understanding, overall satisfaction) and learning goals (i.e. using intension, related to learning goals, self-confidence improvement, self-satisfaction). To validate the model, a set of hypotheses has been assumed about how various constructs would be related to one another. The assumption is that there is a relationship between the user interface and the impression of the recommender on the user. This impression would raise the system efficiency. As a result, the user would achieve his or her learning goals in a better manner [45]. The corresponding conceptual model is illustrated in Figure 4.

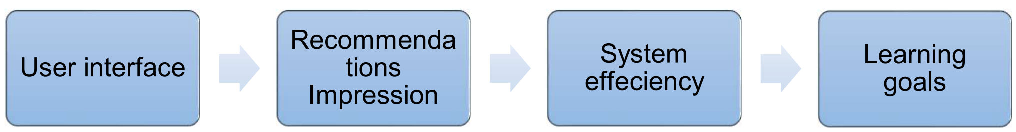


Figure 4 The Conceptual model of the evaluation framework with hypothesized influence paths.

It has been assumed that a recommendation user interface and the interaction adequacy and quality would have positive effects on the users' beliefs in the recommender. As a result, it would eventually lead to users' behavioural intentions. The intentions could be (i) using the system again, (ii) suggesting the system to others, or (iii) using the recommended links for their self-learning goals [45]. The hypotheses of the present study were tested based on the data collected with *structural equation modelling* (SEM) [89]. SEM is a second-generation multivariate statistical analysis used as a statistical technique to test and evaluate casual correlations in a more impressive manner. It includes two levels of analysis: the measurement model and the structural model. The first interprets how hypothetical constructs are measured in terms of the observed variables, and the second level checks the correlations among the constructs [90]. It is worth mentioning that there is no limitation for sample size in PLS [91], and it can run with fewer than 100 samples.

In the next step, the reliability and the validity of psychometric questionnaires, data gathering, and statistical analysis were evaluated. The Proof for the questions has been achieved through the factor analysis and testing the model's fitness using the structural equation methods on the SmartPls [92] software (Figure 5). A structural equation checks the correlations among the constructs [90].

The reliability of the measurements was estimated using the Cronbach's α coefficients on each construct element (Table 4). The numbers have been computed by SmartPls software. Generally, the minimum required value of the Cronbach's α coefficient is 0.7 [93]. Cronbach's α coefficients of the four constructs of the model turned out more than 0.7. Therefore, the measurements of this study can be considered acceptable in terms of reliability.

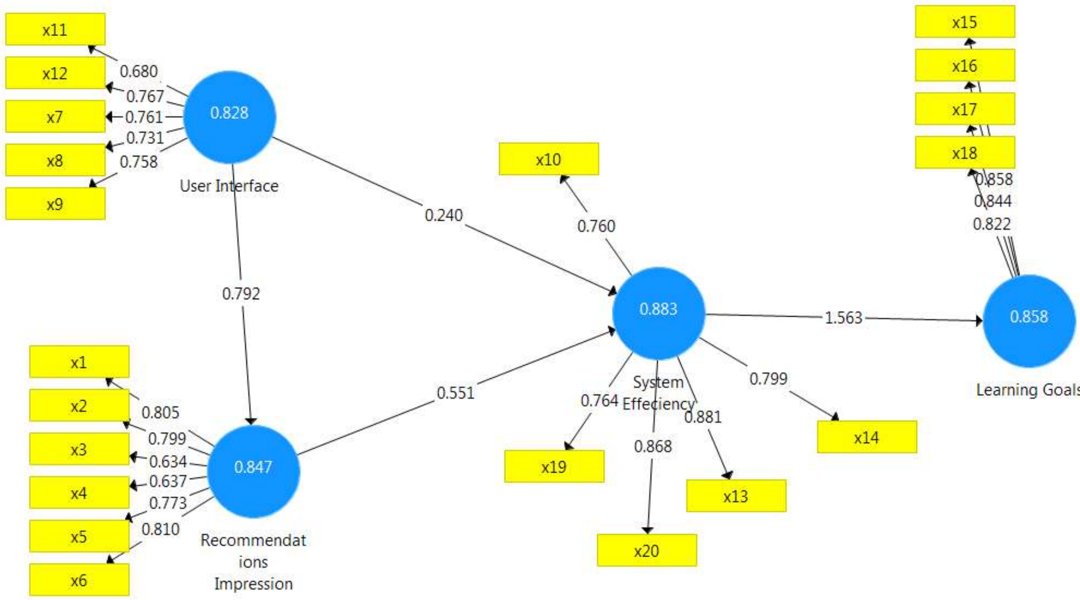


Figure 5 Structural model-path coefficients.

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Learning Goals	0.86	0.86	0.90	0.70
System Efficiency	0.87	0.88	0.91	0.67
Type of Recommendations	0.84	0.85	0.88	0.56
User Interface	0.80	0.83	0.86	0.55

Table 4 Total Construct Reliability and Validity.

Additionally, the validity of the measurements was verified. Fornell and Larcker's measure of average variance extracted (AVE) has been used for this purpose [94]. The AVE determines the amount of variance apprehended by a construct through its factors relative to the amount of variance as a result of the measurement error. The AVEs for all the four constructs are more than 0.5 [91, 93](Figure 5). Therefore, the convergent validity of the four constructs can be considered acceptable. Generally speaking, there were acceptable reliability and validity in the measurements of this study.

Moreover, the composite reliability to be acceptable, the CR coefficients should be more than 0.7. This value represents a good fit in terms of the composite reliability. The coefficient of determination, R^2, is the most significant index to assess a structural model. It shows the influence of exogenous variables on endogenous variables, and three values of 0.19, 0.33, and 0.67 are considered as the criterion for weak, medium, and strong amounts of R^2 respectively [95]. Based on the results of R Square Adjusted (Figure 6), the estimated path proved to be acceptable.

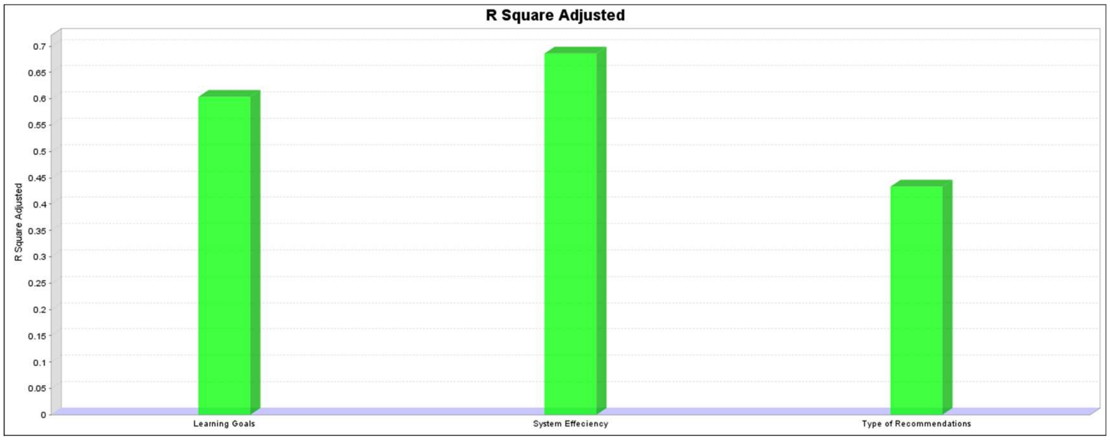


Figure 6 R Square Adjusted values.

9 Conclusion

The primary contribution of this research is to introduce a resource-based recommender system that accommodates the features of educational web pages according to the individual user's learning style. On this basis, a new approach, in the form of a web page ranking formula, has been proposed. Computation of the learning style dimensions is based on Felder-Silverman theory. The users' search query and their learning style would be adapted to features of the educational web pages and their metadata. In other words, learning style dimension values were taken into account in the proposed page ranking formula. To increase the suitability of the recommendations, a formal approach has been proposed to overcome the grey-sheep problem. A grey-sheep user has peculiar preferences. So, by this consideration, each page is ranked for every user based on his or her learning style. A user's opinion and satisfaction about the suitability of every web page as a recommended result was submitted to the developed system. The system used the user's feedback to deliver the best recommendations. Moreover, it ranked the sample OCW's web pages based on the query-dependent score of each page and its query-independent score. Afterwards, the same process is carried out by using our proposed method as the ranking formula. The system suitability has been evaluated by a group of academic students. To validate our idea, a set of hypotheses about how the various constructs relate to each other is built. The results show that the proposed method outperforms the general search algorithm. This system can be used as a template at formal and informal learning and educational environments for resource-based learning.

References

1. Manouselis, N., et al., *Recommender Systems for Technology Enhanced Learning: Research Trends and Applications*. 2014: Springer Science & Business Media.

2. Ricci, F., L. Rokach, and B. Shapira, *Introduction to recommender systems handbook*. 2011: Springer.
3. Drachsler, H., et al., *Panorama of recommender systems to support learning*, in *Recommender systems handbook*. 2015, Springer. p. 421-451.
4. Adomavicius, G. and A. Tuzhilin, *Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions.* Knowledge and Data Engineering, IEEE Transactions on, 2005. **17**(6): p. 734-749.
5. Bobadilla, J., et al., *Recommender systems survey.* Knowledge-Based Systems, 2013. **46**: p. 109-132.
6. Klašnja-Milićević, A., et al., *E-Learning personalization based on hybrid recommendation strategy and learning style identification.* Computers & Education, 2011. **56**(3): p. 885-899.
7. Manouselis, N., et al., *RecSysTEL preface 2010.* Procedia Computer Science, 2010. **1**(2): p. 2773-2774.
8. Verbert, K., et al., *Context-aware recommender systems for learning: a survey and future challenges.* Learning Technologies, IEEE Transactions on, 2012. **5**(4): p. 318-335.
9. Vesin, B., et al., *Applying Recommender Systems and Adaptive Hypermedia for e-Learning Personalizatio.* Computing and Informatics, 2013. **32**(3): p. 629-659.
10. Lam, X.N., et al. *Addressing cold-start problem in recommendation systems*. in *Proceedings of the 2nd international conference on Ubiquitous information management and communication*. 2008. ACM.
11. Gras, B., A. Brun, and A. Boyer. *Identifying Grey Sheep Users in Collaborative Filtering: a Distribution-Based Technique*. in *Proceedings of the 2016 Conference on User Modeling Adaptation and Personalization*. 2016. ACM.
12. Ossenbruggen, J.R., *Processing Structured Hypermedia-A Matter of Style*. 2001.
13. Brusilovsky, P. and M.T. Maybury, *From adaptive hypermedia to the adaptive web.* Communications of the ACM, 2002. **45**(5): p. 30-33.
14. Brusilovsky, P., *Methods and techniques of adaptive hypermedia.* User modeling and user-adapted interaction, 1996. **6**(2-3): p. 87-129.
15. Brusilovsky, P., A. Kobsa, and J. Vassileva, *Adaptive hypertext and hypermedia*. 1998: Springer.
16. Somyürek, S., *The new trends in adaptive educational hypermedia systems.* The International Review of Research in Open and Distributed Learning, 2015. **16**(1).
17. Henze, N. and W. Nejdl, *Adaptation in open corpus hypermedia.* International Journal of Artificial Intelligence in Education, 2001. **12**(4): p. 325-350.
18. Henze, N. and W. Nejdl. *Logically characterizing adaptive educational hypermedia systems*. in *International Workshop on Adaptive Hypermedia and Adaptive Web-based Systems (AH 2003)*. 2003.
19. Triantafillou, E., A. Pomportsis, and S. Demetriadis, *The design and the formative evaluation of an adaptive educational system based on cognitive styles.* Computers & Education, 2003. **41**(1): p. 87-103.
20. Brusilovsky, P., *Developing adaptive educational hypermedia systems: From design models to authoring tools*, in *Authoring tools for advanced technology Learning Environments*. 2003, Springer. p. 377-409.
21. Kamceva, E. and P. Mitrevski, *On the general paradigms for implementing adaptive e-learning systems.* ICT Innovations, 2012 Web Proceedings. Ohrid, Macedonia, 2012: p. 281-289.
22. Jannach, D., et al., *Recommender systems: an introduction*. 2010: Cambridge University Press.
23. Isinkaye, F., Y. Folajimi, and B. Ojokoh, *Recommendation systems: Principles, methods and evaluation.* Egyptian Informatics Journal, 2015. **16**(3): p. 261-273.

24. Tintarev, N. and J. Masthoff. *A survey of explanations in recommender systems*. in *Data Engineering Workshop, 2007 IEEE 23rd International Conference on*. 2007. IEEE.
25. Verbert, K., et al., *Context-aware recommender systems for learning: a survey and future challenges.* IEEE Transactions on Learning Technologies, 2012. **5**(4): p. 318-335.
26. Balabanović, M. and Y. Shoham, *Fab: content-based, collaborative recommendation.* Communications of the ACM, 1997. **40**(3): p. 66-72.
27. Pazzani, M.J. and D. Billsus, *Content-based recommendation systems*, in *The adaptive web*. 2007, Springer. p. 325-341.
28. Lops, P., M. De Gemmis, and G. Semeraro, *Content-based recommender systems: State of the art and trends*, in *Recommender systems handbook*. 2011, Springer. p. 73-105.
29. Su, X. and T.M. Khoshgoftaar, *A survey of collaborative filtering techniques.* Advances in artificial intelligence, 2009. **2009**: p. 4.
30. Herlocker, J.L., et al., *Evaluating collaborative filtering recommender systems.* ACM Transactions on Information Systems (TOIS), 2004. **22**(1): p. 5-53.
31. Burke, R., *Hybrid recommender systems: Survey and experiments.* User modeling and user-adapted interaction, 2002. **12**(4): p. 331-370.
32. Burke, R., *Hybrid web recommender systems*, in *The adaptive web*. 2007, Springer. p. 377-408.
33. Castellano, G., A.M. Fanelli, and M.A. Torsello, *NEWER: A system for NEuro-fuzzy WEb Recommendation.* Applied Soft Computing, 2011. **11**(1): p. 793-806.
34. Drachsler, H., *Navigation support for learners in informal learning networks*. 2009.
35. Santos, O.C. and J.G. Boticario, *Modeling recommendations for the educational domain.* Procedia Computer Science, 2010. **1**(2): p. 2793-2800.
36. Paulsen, M.F., *Experiences with Learning Management Systems in 113 European Institutions.* Educational Technology & Society, 2003. **6**(4): p. 134-148.
37. Manouselis, N., et al., *Recommender systems for learning*. 2012: Springer Science & Business Media.
38. Tang, T.Y. and G. McCalla. *Smart recommendation for an evolving e-learning system*. in *Workshop on Technologies for Electronic Documents for Supporting Learning, AIED*. 2003.
39. Garcia-Molina, H., *Flexible Recommendations in CourseRank*, in *On the Move to Meaningful Internet Systems: OTM 2008*. 2008, Springer. p. 7-7.
40. Felder, R.M. and L.K. Silverman, *Learning and teaching styles in engineering education.* Engineering education, 1988. **78**(7): p. 674-681.
41. Froschl, C., *User modeling and user profiling in adaptive e-learning systems.* Graz, Austria: Master Thesis, 2005.
42. Chrysafiadi, K. and M. Virvou, *Advances in Personalized Web-Based Education*. 2015: Springer.
43. Brusilovski, P., A. Kobsa, and W. Nejdl, *The adaptive web: methods and strategies of web personalization*. Vol. 4321. 2007: Springer Science & Business Media.
44. Brusilovsky, P. and E. Millán. *User models for adaptive hypermedia and adaptive educational systems*. in *The adaptive web*. 2007. Springer-Verlag.
45. Pu, P., L. Chen, and R. Hu. *A user-centric evaluation framework for recommender systems*. in *Proceedings of the fifth ACM conference on Recommender systems*. 2011. ACM.
46. Kobsa, A., *Generic user modeling systems.* User modeling and user-adapted interaction, 2001. **11**(1-2): p. 49-63.
47. de Koch, N.P., *Software engineering for adaptive hypermedia systems*. 2001, PhD Thesis, Verlag Uni-Druck, Munich.
48. Martins, C., et al., *User Modeling in Adaptive Hypermedia Educational Systems.* Educational Technology & Society, 2008. **11**(1): p. 194-207.

49. Dunn, R., J.S. Beaudry, and A. Klavas, *Survey of research on learning styles.* California Journal of Science Education, 2002. **2**(2): p. 75-98.
50. Dağ, F. and A. Geçer, *Relations between online learning and learning styles.* Procedia-Social and Behavioral Sciences, 2009. **1**(1): p. 862-871.
51. Dunn, R., K. Dunn, and M. Freeley, *Practical applications of the research: Responding to students' learning styles–step one.* Illinois State Research and Development Journal, 1984. **21**(1): p. 1-21.
52. Riding, R. and I. Cheema, *Cognitive styles—an overview and integration.* Educational psychology, 1991. **11**(3-4): p. 193-215.
53. Graf, S., *Adaptivity in learning management systems focussing on learning styles*. 2007, Vienna University of Technology.
54. Behaz, A. and M. Djoudi, *Adaptation of learning resources based on the MBTI theory of psychological types.* IJCSI International Journal of Computer Science Issues, 2012. **9**(1): p. 135-141.
55. Jonassen, D.H. and B.L. Grabowski, *Handbook of individual differences, learning, and instruction*. 2012: Routledge.
56. Kappe, F., et al., *A predictive validity study of the Learning Style Questionnaire (LSQ) using multiple, specific learning criteria.* Learning and Individual differences, 2009. **19**(4): p. 464-467.
57. Cassidy*, S., *Learning styles: An overview of theories, models, and measures.* Educational psychology, 2004. **24**(4): p. 419-444.
58. Solomon, B.A. and R.M. Felder, *Index of learning styles*. 2006.
59. *Index of Learning Styles*. 2016; Available from: http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSpage.html.
60. Graf, S., et al., *In-depth analysis of the Felder-Silverman learning style dimensions.* Journal of Research on Technology in Education, 2007. **40**(1): p. 79-93.
61. Özpolat, E. and G.B. Akar, *Automatic detection of learning styles for an e-learning system.* Computers & Education, 2009. **53**(2): p. 355-367.
62. Truong, H.M., *Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities.* Computers in Human Behavior, 2016. **55**: p. 1185-1193.
63. Tahmasebi, M. and M. Esmaeili, *Hybrid Adaptive Educational Hypermedia Recommender Accommodating User's Learning Style and Web Page Features.* Journal of AI and Data Mining, 2018.
64. Radwan, N., *An Adaptive Learning Management System Based on Learner's Learning Style.* International Arab Journal of e-Technology, 2014. **3**(4): p. 7.
65. Lee, M., *Utilizing the Index of Learning Styles (ILS) in a technology-based publishing program*. 2009, University of Phoenix.
66. Mohammadi, H., et al. *A bi-section graph approach for hybrid recommender system*. in *Granular Computing (GrC), 2011 IEEE International Conference on*. 2011. IEEE.
67. Litzinger, T.A., et al., *A psychometric study of the index of learning styles©.* Journal of Engineering Education, 2007. **96**(4): p. 309.
68. Olston, C. and M. Najork, *Web crawling.* Foundations and Trends in Information Retrieval, 2010. **4**(3): p. 175-246.
69. Najork, M., *Web crawler architecture*, in *Encyclopedia of Database Systems*. 2009, Springer. p. 3462-3465.
70. Najork, M. and A. Heydon, *High-performance web crawling*. 2002: Springer.
71. Chakrabarti, S., M. Van den Berg, and B. Dom, *Focused crawling: a new approach to topic-specific Web resource discovery.* Computer Networks, 1999. **31**(11): p. 1623-1640.

72. Manning, C.D. and P. Raghavan, *An introduction to information retrieval*. 2009, Cambridge University Press.
73. Global network of educational institutions, i.a.o. *The Open Education Consortium | The Global Network for Open Education*. 2016; Available from: http://www.oeconsortium.org.
74. *Alexa - Actionable Analytics for the Web*. 2016; Available from: http://www.alexa.com/.
75. Felder, R.M., *Matters of style.* ASEE prism, 1996. **6**(4): p. 18-23.
76. Buder, J. and C. Schwind, *Learning with personalized recommender systems: A psychological view.* Computers in Human Behavior, 2012. **28**(1): p. 207-216.
77. Akbulut, Y. and C.S. Cardak, *Adaptive educational hypermedia accommodating learning styles: A content analysis of publications from 2000 to 2011.* Computers & Education, 2012. **58**(2): p. 835-842.
78. El-Bishouty, M.M., et al., *Teaching Improvement Technologies for Adaptive and Personalized Learning Environments*, in *Ubiquitous Learning Environments and Technologies*. 2015, Springer. p. 225-242.
79. PHAM, Q.D. and A.M. FLOREA, *A method for detection of learning styles in learning management systems.* UPB Scientific Bulletin, Series C: Electrical Engineering, 2013. **75**: p. 3-12.
80. Salton, G., *The SMART retrieval system—experiments in automatic document processing.* 1971.
81. Robertson, S.E. and S. Walker. *Some simple effective approximations to the 2-poisson model for probabilistic weighted retrieval*. in *Proceedings of the 17th annual international ACM SIGIR conference on Research and development in information retrieval*. 1994. Springer-Verlag New York, Inc.
82. Page, L., et al. *The Pagerank Algorithm: Bringing Order to the Web*. in *Proceedings of the International Conference on the World Wide Web*. 1998.
83. Bidoki, A.M.Z. and N. Yazdani, *DistanceRank: An intelligent ranking algorithm for web pages.* Information Processing & Management, 2008. **44**(2): p. 877-892.
84. Felder, R.M. and B.A. Soloman, *Index of learning styles (ILS).* On-line at http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSpage.html, 1999.
85. Erdt, M., A. Fernandez, and C. Rensing, *Evaluating recommender systems for technology enhanced learning: A quantitative survey.* IEEE Transactions on Learning Technologies, 2015. **8**(4): p. 326-344.
86. consultant, K.T.-L.a.S., *Basic Concepts - Lucene Tutorial.com.* 2017.
87. Tuan*, H.L., C.C. Chin, and S.H. Shieh, *The development of a questionnaire to measure students' motivation towards science learning.* International Journal of Science Education, 2005. **27**(6): p. 639-654.
88. Venkatesh, V., et al., *User acceptance of information technology: Toward a unified view.* MIS quarterly, 2003: p. 425-478.
89. Hooper, D., J. Coughlan, and M. Mullen, *Structural equation modelling: Guidelines for determining model fit.* Articles, 2008: p. 2.
90. Anderson, J.C. and D.W. Gerbing, *Structural equation modeling in practice: A review and recommended two-step approach.* Psychological bulletin, 1988. **103**(3): p. 411.
91. Hair, J.F., C.M. Ringle, and M. Sarstedt, *PLS-SEM: Indeed a silver bullet.* Journal of Marketing theory and Practice, 2011. **19**(2): p. 139-152.
92. Wong, K.K.-K., *Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS.* Marketing Bulletin, 2013. **24**(1): p. 1-32.
93. Latan, H. and I. Ghozali, *Partial least Squares: Concept and application path modeling using program XLSTAT-PLS for empirical research.* BP UNDIP, 2012.

94. Fornell, C. and F.L. Bookstein, *Two structural equation models: LISREL and PLS applied to consumer exit-voice theory.* Journal of Marketing research, 1982: p. 440-452.
95. Cohen, J., *A power primer.* Psychological bulletin, 1992. **112**(1): p. 155.