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# Hybrid Adaptive Educational Hypermedia Recommender Accommodating User's Learning Style and Web Page Features

M. Tahmasebi[1], F. Fotouhi Ghazvini[2*] and M. Esmaili[3]

*1. Department of Computer Engineering, Yazd University and University of Qom, Qom, Iran.*
*2. Department of Computer Engineering and IT, University of Qom, Qom, Iran.*
*3. Department of Computer Engineering, Azad University of Kashan, Kashan, Iran.*

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**Corresponding author: f-fotouhi@qom.ac.ir (F. Fotouhi Ghazvini).*

**Abstract**
Personalized recommenders have proved to be of use as a solution to reduce the *information overload* problem. Especially in Adaptive Hypermedia System, a *recommender* is the main module that delivers suitable learning objects to learners. Recommenders suffer from the cold-start and the sparsity problems. Furthermore, obtaining learner's preferences is cumbersome. Most studies have only focused on similarity between the interest profile of a user and those of others. However, it can lead to the *gray-sheep problem*, in which users with consistently different opinions from the group do not benefit from this approach. On this basis, matching the learner's learning style with the web page features and mining specific attributes is more desirable. The primary contribution of this research work is to introduce a feature-based recommender system that delivers educational web pages according to the user's individual learning style. We propose an Educational Resource recommender system that interacts with the users based on their learning style. The learning style determination is based on the Felder-Silverman theory. Furthermore, we incorporate all the explicit/implicit data features of a web page and the elements contained in them that have an influence on the quality of recommendation, and help the system make more effective recommendations.

**Keywords:** *Adaptive Educational Hypermedia, Individual Learning Styles Detection, Learner Modeling, Web Page Feature, Web Page Ranking, Recommendation Systems, Web Mining.*

## 1. Introduction

"Technology Enhanced Learning (TEL) aims to design, develop, and test socio-technical innovations that will support and enhance learning practices of both the individuals and organizations. It is an application domain that generally addresses all types of technology research and development aiming to support teaching and learning activities" [1, 2]. TEL [3] includes the recommendation technologies that facilitate the retrieval of relevant learning resources. This type of system has been designed to overcome the information overloading problem by the tremendous growth of the existing users and online materials. The recommender systems make up an extensively studied and well-established field of research and application [4]. They have been reviewed vastly in several surveys of the state-of-the-art [5, 6]. In 2007, the first efforts to create opportunities for researchers working on topics related to recommender systems for TEL found their way in workshops (such as the workshop on "Social Information Retrieval for Technology Enhanced Learning", "Context-Aware Recommendation for Learning", and "Towards User Modeling and Adaptive Systems for All") [1]. Recommenders play an important role in helping learners to identify the relevant information and suitable resources from a potentially wide variety of choices buried in a large amount of irrelevant materials [7]. However, there are some aspects and features that must be considered in learning environments. These aspects must be distinguished from noneducational systems. The TEL area offers some specific characteristics that are not met by the today's general-purpose recommendation approaches. Therefore, the algorithms underlying regular recommender systems are not directly transferable [8]. The learner often utilizes his/her own tools, methods, collaborative styles, and processes. TEL recommendation systems must support learners by providing them with relevant educational contents and predicting their requirements in response to their traits, behavior, profiles, history logs, and pedagogical aspects [9]. In this context, an intelligent agent delivers sophisticated recommendations based on the user's previous actions, profile, and characteristics. As a result, huge amounts of the user data and his/her activities are required to make accurate recommendations. However, in TEL, many learning activities take place with just a few learners to participate. The learner's context and characteristics must, therefore, be considered in a much more specific way than devoted in the today's recommendation approaches. Obviously, data for recommendation algorithms can be based upon gathering explicit and implicit attributes of learners and resource learning materials. The main contribution of this work is to improve the quality of recommendations by investigating the possibility of collating user traits and web page features to deliver the best educational resources to every user. By identifying the user's learning style, his/her learning habits and knowledge can be deducted. Therefore, appropriate web pages containing necessary items can be delivered.

## 2. Adaptive educational hypermedia

Hypermedia is a combination of 'hypertext' and 'multimedia'. A hypertext system is a complex piece of software consisting of several parts that serve a very different purpose [10]. According to the 'Oxford Advanced American Dictionary', the term 'adaptive' is defined as "to be able to change when necessary in order to deal with different situations". Therefore, an adaptive system adapts itself or another system to various circumstances. The process of adaptation is based on the user's preferences and goals. The user's properties are stored in a profile or in a model of the user. The system constructs the user model and provides the user detailed preferences. The 'Adaptive Hypermedia System' started around 1990 [11]. Nowadays many industries and sites use different kinds of adaptive systems. The introduction of the web in 1996 with its great impact on hypermedia has brought about a major turning point in the adaptive system's evolution. Peter Brusilovsky gave an overview of adaptive hypermedia systems in 1996 [12]. He defined adaptive hypermedia systems as "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; and it should be able to adapt the hypermedia using this model" [13]. Generally speaking, it is useful in any situation to benefit from hypertext and hypermedia. One kind of the most popular research area for these systems is the Adaptive Educational Hypermedia (AEH) system [14]. As the name suggests, it is applied in the context of education, and offers students customized educational content in e-learning environments. It customizes itself according to the users' needs and capabilities to minimize the perplexity and cognitive overload problems of learners and to maximize learning efficiency by providing hyperlinks that are most related to the user. Educational technology, intelligent tutoring systems, cognitive science, and computer engineering are some examples of different research fields that are devoted to the development of AEH systems. The objective is not to have stand-alone systems: AEH has been developed to overcome the one-size-fits-all problem [1] in traditional e-learning and intelligent tutoring systems. Moreover, it is not limited to formal or informal education or training efforts. According to Henze and Nejdl [15], an AEH system consists of a document space, a user model, observations, and an adaptation component. The document space belongs to the hypermedia system and is enriched with associated information (e.g. annotations, domain graphs or knowledge graphs). The user model stores, describes, and infers information, knowledge, and preferences about a user. Observations represent the information about the interaction between the user and the system. These observations are used for updating the user model [16]. Thus a common architecture for an adaptive educational system indicates that it has four essential and intern dependent components, as follow:

1- Domain model: It is a set of domain concepts. Each concept has some topics that represent individual pieces of knowledge for each domain, and their size depends on the domain. Topics are linked to one another forming a semantic network as the structure of the knowledge domain.

2- Student model: It consists of a personal, cognitive, and student knowledge profile. It should accurately reflect the characteristics of different users [17, 18].
3- Content model: It describes the educational contents in terms of the domain model concepts. The simplest content model relates every content item to exactly one domain concept [18].
4- Adaptation module: To support adaptivity, it displays information to the user based on her/his cognitive preferences [17].

In the following section, one of the most important applications of this system, namely recommender systems, will be introduced.

## 3. Recommender systems

With the rapid growth of the web, the recommender systems play an important role in helping users find thedesired information [19]. Web Recommender Systems help users make decisions in this complicated information space, where there is an enormous amount of information available to them [20]. Seven advantages of using the recommender systems have been presented by Tintarev and Masthoff [21]. Recently, a number of web page recommender systems have been widely implemented in various domains, especially in the Technology Enhanced Learning domain, to anticipate the information needs of users and to facilitate and personalize their navigation. They became an independent research area in the mid-1990s [2], and have been researched and employed extensively over the last decade. Development of such systems is a multi-disciplinary effort that involves experts from various fields such as Artificial Intelligence, Human Computer Interaction, Information Technology, Data Mining, Statistics, Adaptive User Interfaces, Decision Support Systems, Marketing, and Consumer Behavior [2]. Several recommendation algorithms such as content-based filtering [22-24], collaborative filtering [25, 26], and their hybridizations [27, 28] have been widely discussed in several surveys of the state-of-the-art [5]. While content-based methods recommend items similar to the ones user preferred in the past, collaborative filtering-based methods predict the user interests directly from other users with similar interests and preferences in the past [25]. Hybrid methods combine these two methods to improve recommender performance [6, 28]. A discussion of the advantages and disadvantages of these techniques for TEL has been presented in [1]. Recommender systems are strongly domain-dependent [29] so these algorithms and specific requirements usually cannot be used directly in educational recommenders [30]. Today, recommender systems are considered as an important part of TEL environments. It is generally accepted that this type of systems has been designed to overcome the information-overloading problem by the tremendous growing number of existing users and materials.

In the next section, the particularities of TEL domain for the recommendation and existing work in this area would be argued.

### 3.1. Particularities of TEL for recommendation

Major e-commerce sites and most search engines have joined the recommendation technology in their services in order to personalize their results. As mentioned earlier, unfortunately, the general purpose approaches underlying these regular recommender systems are not directly transferable to the area of TEL [8, 30] because their operations are different from choosing items. Learning is a process that often takes more time and interactions than a commercial transaction, and therefore, learners rarely achieve the end-state after a fixed time. In addition to the personalized needs of this area, learning activities take place in special environments that are composed of different tools and systems. For example, in a learning management system (LMS) [31], there is a possibility to have an access to learning resources and collaboration facilities. However, it does not ensure that learners exclusively use them; rather, they often use additional tools to find resources. Therefore, in such environments, the learner's progress and activities must be tracked. Pedagogical approaches are another consideration that makes learning situations more complex. For instance, for learners with no prior knowledge in a particular domain, relevant pedagogical rules such as Vygotsky's zone of proximal development can be applied, e.g. "recommended learning objects should have a level slightly above the learners' current competence level" [32]. In such scenarios, what is important is to identify the relevant learning goals and supporting learners in attaining those goals. This is how using recommender systems in TEL makes its application quite different. A recent survey of this application has been presented by Manouselis et al. [1]. Most implemented systems suggest learning resources [33]. Course recommenders [34] typically provide advice to learners on suitable courses. Most TEL recommenders rely on the profiles of learners. The knowledge level of the learner and learning styles, often based on the Felder-Silverman [35] inventory, are used to personalize recommendations. Furthermore, some systems rely on resource features that describe multiple attributes of resources like multimedia facilities, audio, video, graph, and charts. In addition to the general characteristics like author, title, and keywords, many systems use educational metadata that describes, for instance, the difficulty level of a resource.

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

## 4. User modeling

A user model is an internal representation of the user's information and preferences [36]. In other words, it is the system's knowledge about the user that allows expressing and extracting conclusions on the user's characteristics. As mentioned earlier, one distinctive feature of an adaptive system, especially an adaptive educational system [37], is a user model [38, 39]. Adaptive Hypermedia is generally referred to as a cross-road in the research of user modeling, and it has been recognized that user modeling plays a main role in the success of recommender systems [40]. User Modeling is usually traced back to the works of Allen, Cohen, Perrault, and Elaine Rich [41]. The user model must represent the required characteristics of the user regarding the context of the application. Koch describes the application of user models as follows: "Users are different: they have different backgrounds, different knowledge about a subject, and different preferences, goals, and interests. In order to individualize, personalize or customize actions, a user model is needed that allows for selection of individualized responses to the user" [36]. Therefore, wherever an individualized response of the system is expected, a user model should be applied. Different types of applications like adaptive e-learning systems and recommenders can benefit from user models. Furthermore, not only the attributes of a user (e.g. domain knowledge, preferences, and goals) but also limitations (e.g. disabilities like color blindness) of the user's perception must be considered within a user model. If these limitations have to be violated, it is important to know the least disturbing options [36]. The terms user profiling and user modeling are often used as interchangeable synonyms. Koch has described a user profile as a simple user model [42]. A user profile is a collection of personal information that is stored without adding a further description or interpreting. User profiles represent intellectual abilities and intentions, cognitive skills, learning styles, preferences, and interactions with the system. These properties are stored after assigning them values that may be final or change over time [39, 43]. Depending on the content and the amount of information about the user, which is stored in the user profile, a user can be modeled. Thus the user profile is used to retrieve the required information to build up a model of the user. In this research work, the following types of data were collected for building a user's profile, with an explicit representation:

1- Generic data including personal information (e.g. name, surname, email, password, gender, nationality, language preference, etc.), demographic data (e.g. birth date), and academics background (e.g. educational field and level, and background knowledge)
2- Psychological data including the learning style and cognitive capacities.

In the case of a hybrid recommender, in addition to the users' characteristics, their past ratings with similar preferences and operations are largely combined to improve the recommendation procedure. Therefore, cognitive styles must be considered for this type of system.

### 4.1. Learning and cognitive style theory

The learning style concept was first used by R. Dunn in 1960 [44]. Learning styles can be defined as unique manners in which learners begin to concentrate on, process, absorb, and by which they retain new and difficult information [45]. A general and accepted concept is that everyone differs in learning. Every individual has different learning styles, which means that s/he receives and interprets data through different mental filters [46]. Learning style is the way a person perceives and organizes information [47]. It describes learner's preferences for different types of learning and instructional activities [48]. Thus it can be defined as learner's beliefs, priorities, and preferred behaviors toward the tutor and other learners, course content, ways of information processing and responses, use of educational motivations, willingness towards learning, and adjustment in the learning environment. Also it is a specific way of acquiring knowledge, which is concerned with the practical matters of the learning environment [49], and it has an impact on achievement and quality of learning results [50]. Some students understand by images. Others may prefer texts and readings. Some may deal well with theories, while others learn through observation and examples. Diagnosing the learning style is the best way to obtain information about the learners, and based on the learning theories, everybody has a specific learning style. Utilizing it in any educational system can have a tremendous effect on the learning and teaching quality [44]. Accordingly, learning styles tend to be more or less stable but they can be changed over time. One of the most widely used models regarding those styles is the Index of Learning Styles (ILS) [51], developed by Richard Felder and Linda Silverman in 1988. They designed a model (known as FSLSM) for basic science and engineering students. It divides learners more accurately and has the best parameters for personalization that combines several major learning style models [35, 44, 52]. In Figure 1, the chart shows the distribution of learning style theories employed in adaptive learning system as in [53].

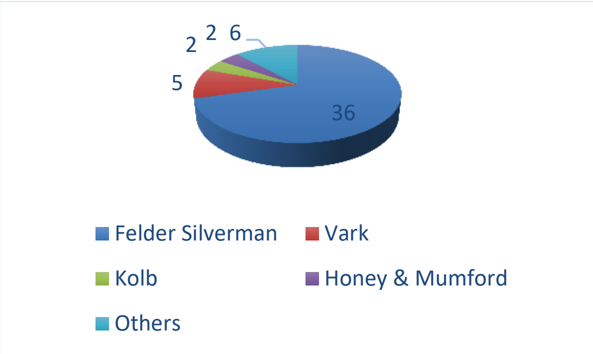


**Figure 1. Learning style theories applied in adaptive learning system.**

Active/Reflective, Global/Sequential, Inductive/Deductive, Sensitive/Intuitive, and Visual/Oral are five different dimensions that have been defined in this model to distinguish the learners' preferences in the learning style. Other learning style models influence them quite strongly. Active learners learn by doing and working with others. They prefer to manipulate objects, do physical experiments, self-assessment exercises, and multiple questions, guess examinations, and learn by trying, while the reflective ones learn by thinking through and working isolated. They evaluate options and learn by analysis and enjoy studying a problem on their own, examples, outlines, summaries, and result pages. Sensing learners like to learn detailed materials and tend to be practical. They seek the facts, and prefer practical, concrete, examples, explanation, facts, and procedural information, whereas intuitive learners prefer to learn abstract subjects such as theories, definitions, algorithms, and their meanings, and tend to be more innovative than sensing. Visual learners remember best what they have seen. Thus they prefer graphs, pictures, diagrams, charts, videos, animations, schematics, and materials in a visual representation. On the other hand, verbal learners like written or spoken explanations with words like those in texts or audio stuffs; 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.

Identification and understanding a learner's preferences and dimensions [54, 55] help us choose an appropriate web page for recommendation. Most learning and teaching style components parallel one another [35]. Active learners do not learn much in situations that require them to be passive; rather, they enjoy working in groups to figure out problems. In contrast, reflective learners do not learn much in situations that provide no opportunity to think about the information being presented; rather, they enjoy figuring out a problem on their own. For example, a student who favors intuitive over sensory perception would respond well to materials including concepts rather than facts. A student who favors visual perception would be most comfortable with courses that use charts, pictures, and films so that the system can deliver a suitable web page for each one; a page including concepts goes to the first and a page containing multimedia tutorials to the second. In this research work, FSLSM was used to extract the user's learning characteristics. Several types of research works have been conducted on the subject of adaptive learning, as discussed in [56]. A good recommender system adjusts and delivers a web page resource according to the user's characteristics. Therefore, features and parameters of the web pages must be crawled and extracted.

## 5. Web page features

The performance of a recommender model depends on the structure of the crawled websites besides the specific technique that it uses. Figure

2 shows the process of educational resource extraction. Web crawling [57, 58], as an important part of this action, is the process used by the resource gathering section of the system to collect the corresponding pages from the web.

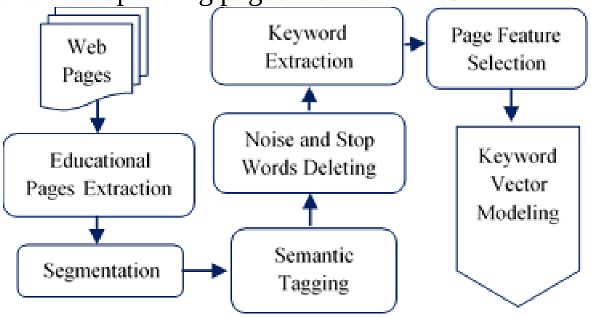


**Figure 2. Educational Resource Extraction Process.**

In order to gather the related resources for the recommender system, a web crawler [57] was used in the present research work. 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 in them, and recursively continues to download the web pages identified by these hyperlinks. Designing a web crawler is a challenging task. There are tricky performance and reliability issues, and, more importantly, there are even social issues. Crawling is the most fragile application since it involves an interaction with hundreds of thousands of web servers and various name servers, which are all beyond the control of the system. While it is fairly easy to build a slow crawler that downloads a few pages per second for a short period of time, building a high-performance system that can download hundreds of millions of pages over several weeks presents a number of challenges in the system designed, I/O and network efficiency, as well as robustness and manageability. One interesting technique is to perform focused crawling on the web [59]. 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 web 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 [60] search engines but are usually related to the retrieval and monitoring of useful hypertextual information. In this research work, our major concern was not to design a high-performance web crawler [61], and, therefore, we developed a simple web crawler whose architecture is depicted in Figure 3.

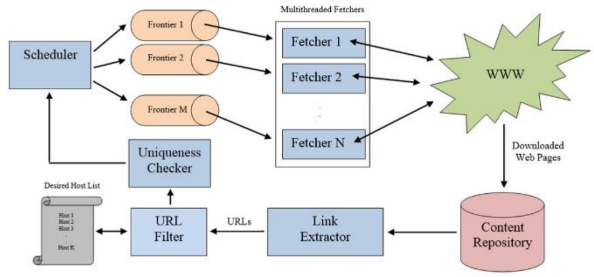


**Figure 3. Simple Crawler Architecture.**

First of all, a number of seed URLs from the desired hosts are injected into the frontiers. A frontier [58] is a queue of URLs scheduled for crawling by the scheduler, which wait to be processed. There are a number of multi-threaded fetchers that take the URLs from the head of frontiers and download them. The downloaded web pages are stored on a disk in a content repository. The link extractor is responsible for parsing and extracting all the links from a given HTML page persisted in the repository. In order to ensure that all the links found belong to the set of desired websites, a *URL Filter* is employed, which matches the host portion of the URL against the list of desired hosts. The *Uniqueness Checker* must check if a URL is present in the repository of the unique URLs and if the corresponding page has already been collected. Finally, the candidate URLs are scheduled into the frontiers based on their hostname in order to be downloaded in a polite way (i.e. there is a so-called *politeness delay* between each connection to a website). As mentioned earlier, in the link extraction part of the crawler, the HTML document is passed to an HTML parser. The HTML parser allows analysis and manipulation of parts of an HTML document in addition to recognizing the mark-up and separating it from the plain text. The plain text is then passed to a tokenizer that goes through a process called *tokenization*. Tokenization [60] is the process of breaking an input text into a stream of meaningful tokens or terms (i.e. an instance of a sequence of characters grouped together as a useful semantic unit for processing). The next step is to drop tokens that would appear to be of little value in helping extract keywords entirely, called *stop words*. Stop words are basically a set of commonly used words in any language, not just English. The reason why stop words are critical to many applications is that if we remove the words that are very commonly used in a given language, we can focus on the important words instead. The general strategy for determining a stop list is sorting the terms by collection frequency (the total number of times each term appears in the document collection), and then taking the most frequent terms, often hand-filtered for their semantic content relative to the domain of the documents being tokenized, as a stop list, the members of which are then discarded during processing. Finally, the output of stop-word removal filtering is injected into a *stemmer*. The goal of stemming is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form. *Stemming* usually refers to a crude heuristic process that chops off the ends of words in the hope of achieving this goal correctly most of the time, and it often includes the removal of derivational affixes. Figure 4 shows how the output of tokenization process is filtered via a *stop-word filter* to generate a more valuable list of terms required for the process of keyword extraction and feature selection.

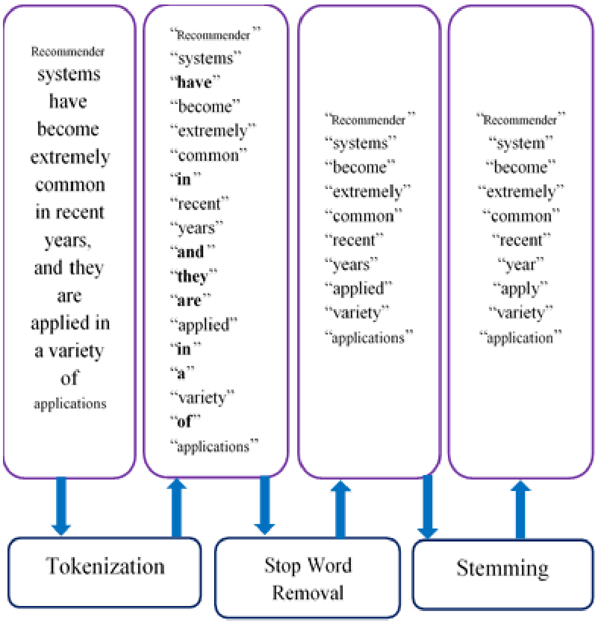


**Figure 4. Tokenization, Stop-Word Removal, and Stemming process of extracted content.**

In our work, we focused on educational pages, especially the Open Courseware Consortium [62], as the recommender resource. We determined these features for selecting the appropriate pages to compare with user style. The domain area subject of the user demand keyword, multimedia facilities, course authority, page visit rate, exercises, update rate and freshness, test and quiz, video, simulation, text, discussion, FAQ, diagram, and image are some of the parameters that we considered for recommendations. At the next step, these features had to be adapted to user styles. For example, for a visual learner, the best page to recommend was the one including simulations, videos, and diagrams, and the worst case was FAQ or text pages.

## 6. Accommodating recommendations with user styles and web page features

In most references, sparsity and cold start have been regarded as the most popular problems for the recommender systems. The sparsity [5, 63] is about the small number of item ratings compared to the total number of items. On the other hand, the cold start deals with the problem of having no knowledge about the new user's preference [64]. There is another problem. Some users with opinions consistently different from the group opinions do not benefit from collaborative algorithms. This is known as *the gray sheep problem* [25, 65-67]. In order to overcome this problem and improve the recommendations, this paper proposes a formal approach in which each web page for every user is ranked based on the user's learning style. Moreover, the learning style dimension values are considered in our recommendations. As mentioned earlier, everyone tends to learn in a diverse and distinct style [44]. Generally, there are two approaches to extract the learners' styles: questionnaire and log file analysis. Regarding the first approach, Felder and Solomon developed a questionnaire with 44 items over 4 dimensions, which totally covers the Felder and Silverman method on learning style [68]. The Index of Learning Styles (ILS) [51] 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 individuals and instructors who wish to use it for teaching and research in their classrooms, and it is licensed to companies and individuals who plan to use it for broader research works or for services to customers or clients. ILS and its information are available in [69]. Table 1 shows the questions of its dimensions [70].

**Table 1. Semantic groups associated with ILS questions of Felder and Solomon.**

| 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 |

Reluctance to answer questions, random guesses, taking too much time, and invalid answers are some problems in the use of questionnaire and answering. Furthermore, uncertainty and noise of answers can be removed by some approaches like the Bayesian [71] network. By applying these techniques, the precision will be improved. The Bayesian network probability is computed based on its theory. Also it can be used to calculate estimations on a user's changing knowledge. The learner's level of knowledge and background in his/her profile, the experts' opinion, and other information would be used as priori probability or the Bayesian network initial value.

As the first step, we designed and developed a web site for the initial assessment of students' learning styles. We gathered the results derived from the questionnaire taken from different students of Yazd universities (Iran) during one semester according to the Felder-Silverman learning and teaching style model. At the next step, the system extracts and computes user's learning style, which is the decision-making parameter for proposing appropriate pages. The computation method is based on [68]. This learning style model is used by another web site that we developed to search against a user's query, for OCW pages, matching the student's style. As stated in Section 7, by crawling the educational web pages, we gather pages relevant to the user search query. Then some features will be extracted from each page that we refer 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 [72] Ranking, Number of Pages on the website, and some Demographic Info (such as words count) are some instances of GPFs. We use a subset of these features for accommodating, and call them Educational Page Feature (EPF).

According to the Learning Styles and Strategies defined by Richard Felder and Barbara Soloman, we assign an adaptation scale between EPFs and each one of the learning style dimensions. We refer to this scale as Goodness Factor (GF). Our proposed GF's are indicated in Table 2. They have been extracted according to [46, 51, 68] and also [73-77]. As an illustration, number zero indicates that the relative EPF is ineffective to 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 of 1 for a visual person. Then page rank of page $P_j$ for user $U_i$ is computed based on (1) and (2):

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

$$\mathrm{UPS}(\mathrm{U_i}.\mathrm{P_j}) = \mathrm{F}\left(\mathrm{UPR}(\mathrm{U_i}.\mathrm{P_j}).\mathrm{GPR}(\mathrm{P_j})\right) \quad (2)$$

where:

- $UPR(U_i.P_j)$ computes ranking of page $P_j$ for user $U_i$;
- $D_{k_{U_i}}$ 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);
- $EPFS(P_j.EPF_l)$ 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);
- $GF(EPF_l.D_k)$ is the Goodness Factor of feature $EPF_l$ against learning style dimension of $D_k$ (extracted from the numbers of Table 2);
- $GPR(P_j)$ 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 [78] and BM25 [79]) and a query-independent score (such as PageRank [80] and DistanceRank [81]);
- $UPS(U_i.P_j)$: In some page ranking situations, if the ranks of two web pages turn out to be the same, an arbitrary general page ranking function like Alexa is used to select the better one and recommend it to the user. Thus UPS computes the Score of Page $P_j$ for User $U_i$ in such situations. Note that the difference between UPS and UPR is that in the UPS computation, GPR of the page is also considered.
- F is an arbitrary function like multiplication. 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).

A search procedure begins with a user-provided query. When users submit course-related search term queries, a subset of OCW pages as learning objects, available in the repository, are selected. This selection is based on pages' content relevance score against the query. Then Equation 1 would be applied to the pages to rank the results based on the user profile. Finally, after sorting the list, twenty documents would be selected by system's agent to display the user, ten based on Equation 1 and the other ten based on the Lucene algorithm. Then the user looks for more promising results. The system aims to generate the best possible outcomes for all users based on their learning styles at any time. Thus it creates different search behaviors for users with different personalities. In order to compute the performance of the proposed method, we get the user's feedback[82].

**Table 2. Relation between Learning Styles Dimensions and Resource Learning Pages.**

| | | 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 |

## 7. Experimental Evaluation

Obviously, measuring a certain property or effect of the recommender system on fitting specified requirements is the goal of any evaluation. Guy Shani and Asela Gunawardana have discussed how evaluation can measure and compare recommenders based on a number of properties that are relevant for different domain areas [83]. Also Drachsler et al. have presented several diverse differences for personalized recommendation to learners as compared to recommendations for users in other domains such as e-commerce applications [84]. Recently, three broad categories of evaluation goals for recommender systems for TEL have been provided [85]. They include measuring recommender system performance, measuring User-Centric effects, and measuring effects on learning. In order to study the effectiveness of Equation 1 and measure User-Centric Effects, a web-based recommender system has been developed. This system is still at the data gathering phase (that includes educational pages crawling and feature extraction, user profile construction, etc.). System evaluation requires another method in the same condition. Thus the retrieval effectiveness of the algorithm will now be compared with the literature on a widely used open source text-search library, Apache Lucene [86]. Apache Lucene index documents in its own inverted index data structure. Its ranking function is based on the vector space model of information retrieval (e.g. the cosine distance between document and query vector) [87]. Recommendations would be presented to users in two separate sections in a graphical user interface (GUI). The first is based on our idea (Equation 1) and the second is based on the Lucene algorithm. Some GPF and EPF features would be displayed to the user. Each feature represents a certain aspect of the site that helps him to decide on an appropriate OCW. Recent studies have shown that 82% of clicked-on documents are relevant to the query topic [88]. Thus getting the user's feedback is a suitable parameter for evaluation. By getting the user's feedback, the accuracy of our formula can be determined. A user's opinion about every web page as a recommended result would be submitted to the system as a single number on a rating scale that is shown in front of each result in a separate column. The system has been evaluated by a group of engineering students to evaluate its accuracy. They have been involved in a learning process in their classrooms during a semester. In order to support their learning, the users are asked to interact with the system and then to rate every recommendation on a 1-to-5-star scale. Their opinions would indicate the suitability of each recommended resource.

For this purpose, the results are evaluated via the following criteria:

- **Averaged Precision (AP)**: AP is determined for query q as the average score of the users, calculated as:

$$\mathrm{AP_q} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{N_q}} \mathrm{score_q(i)}}{\mathrm{N_q}} \tag{3}$$

where $0 \leq score^{q}(i) \leq 5$ shows the score of the $i^{th}$ document in the $q^{th}$ searched quires taken by the user. The score illustrates the users' preference of the recommended OCW.

- **Mean Averaged Precision (MAP):** MAP evaluates the overall performance of the method. We also report the mean AP of all the searched queries as follows:

$$\mathrm{MAP} = \frac{\sum_{q=1}^{N} \mathrm{AP_q}}{\mathrm{N}} \quad (4)$$

where $N$ is the total number of queries.
Figure 5 plots the empirical rating distributions of the user's interest for different search works using AP metric (Equation (3)). The horizontal axis shows the query number. In this figure, our proposed approach is labeled as LSB (depicted by blue lines) and the Lucene method is labeled as RAW (depicted by red dashed lines).

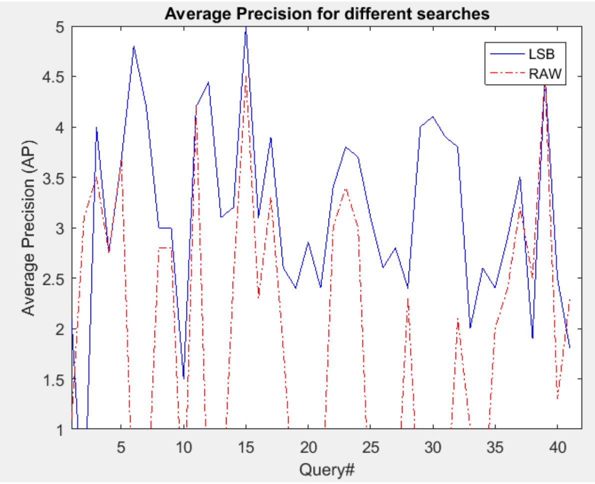


**Figure 5. Average precision of User's feedback for different searches.**

The results obtained illustrate that our proposed method has a better performance than the Lucene method, in most cases.
In order to have a better evaluation, the mean AP (MAP) is also illustrated in Figure 6 (Equation (4)).
According to the results obtained, our proposed method provides considerably better search results for the users.

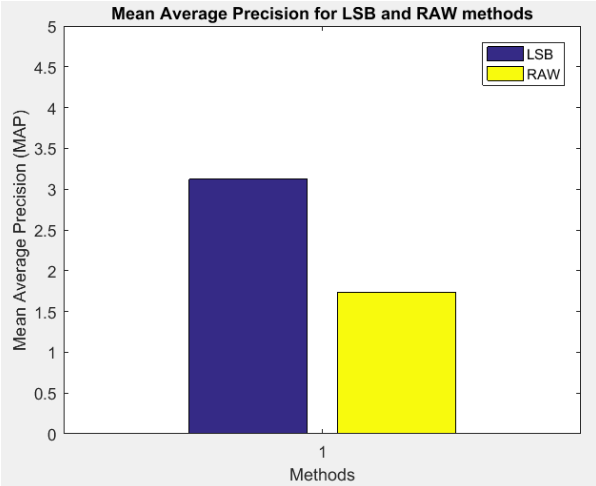


**Figure 6. Mean average precision of Users' feedback for LSB and RAW methods.**

## 8. Conclusion

This paper is a review of the concepts relevant to *adaptive educational recommenders* and *learning styles*. In order to improve the recommendations, we proposed a formal approach to overcome the *gray sheep problem*, in which each page is ranked for every user based on the user's learning style. In other words, the learning style dimension values were considered in our page ranking computations. The objective was to provide a method to help in facilitating the learning process and personalizing the educational resources or resource-based learning. As another contribution, this research work provides some valuable features that are important in the design of such systems. The developed system ranks the educational pages based on a combination of scores computed by considering the query-dependent score of each web page (such as TF-IDF [78], and BM25 [79]) and its query-independent score (such as PageRank [80]). Then the same process was done using our proposed method as the ranking function.

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نشریه هوش مصنوعی و داده کاوی

# پیشنهاد دهنده چند رسانه‌ای آموزشی وفقی مختلط با همسان‌سازی سبک یادگیری کاربر و مشخصات صفحه وب

**محمد طهماسبی[1]، فرانک فتوحی قزوینی[1,*] و مهدی اسماعیلی[2]**

[1] دانشکده فنی مهندسی، دانشگاه قم، قم، ایران.

[2] دانشکده فنی مهندسی، دانشگاه آزاد کاشان، کاشان، ایران.

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**چکیده:**

پیشنهاد دهنده‌های شخصی‌سازی شده، راه حل مناسبی برای کاهش چالش سرباری اطلاعات هستند. مخصوصا در سیستم چندرسانه‌ای وفقی، یک *پیشنهاد دهنده*، ماژول اصلی سیستم است که اشیاء آموزشی مناسب را به فراگیران، ارایه می‌دهد. پیشنهاد دهنده‌ها با دو مشکل شروع سرد و پراکندگی مواجه هستند. علاوه بر این دو چالش کلی، کشف ترجیحات فراگیر، خود معضل دیگری است. اغلب مطالعات فقط بر یافتن تشابه بین علاقه مشترک یک کاربر با دیگر کاربران تمرکز کرده‌اند. اما نتیجه حاصل از آن، برای رفع چالش کاربران معروف به *گوسفند خاکستری*، که دارای نظرات و علایق و نیازهای متفاوت از دیگر افراد هم‌گروهشان هستند، سودی ندارد. بر این اساس، تطابق سبک یادگیری کاربر با مشخصات صفحات وب و استخراج ویژگی‌های مخصوص از آنها، راه حل مطلوب‌تری برای این دسته از کاربران است. نوآوری اصلی این پژوهش در معرفی یک سیستم پیشنهاد دهنده بر اساس ویژگی است، بگونه‌ای که صفحات وب آموزشی را بر طبق سبک یادگیری یک کاربر ارایه می‌دهد. بدین منظور یک سیستم پیشنهاد دهنده منابع آموزشی، طراحی و پیاده‌سازی شده است که با کاربران خود بر اساس سبک یادگیری‌شان تعامل دارد. کشف سبک یادگیری بر اساس تئوری فلدر-سیلورمن انجام می‌گیرد. علاوه بر این، استخراج و ترکیب مشخصات و داده ضمنی و صریح صفحات وب آموزشی با آن، بر کیفیت پیشنهاد اثر داشته و به سیستم در تولید پیشنهادات مفیدتر کمک می‌کند.

**کلمات کلیدی:** چندرسانه آموزشی وفقی، کشف سبک یادگیری فردی، مدل‌سازی فراگیر، مشخصه صفحه وب، رتبه‌بندی صفحه وب، سیستم‌های پیشنهاد دهنده، وب کاوی.