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Adaptivity based on Felder-Silverman Learning Styles Model in E-Learning Systems

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Abstract

Adaptivity in e-learning systems can be provided by efficient modeling of the learners. Learners are modeled based on their individual needs, differences and preferences. In this context, learning styles models are generally used for adaptivity purposes, as they model how the users learn in an effective way. Felder and Silverman learning styles model is the most widely used learning styles model in the e-learning field. How this model can be used to provide adaptivity in e-learning systems is an important research subject. In this paper, this research subject is investigated, by using recent studies on learning styles based adaptive e-learning systems as the basis of the paper. The findings reveal that there are two main research fields in this area; the automatic classification of learners by their learning styles and application of learning styles models to provide adaptive e-learning systems. Some of the research areas that need to be supported with further research studies include; evaluation of the contribution and performance of different data sources and attributes used in learning styles prediction models and tools; and comparison and combination of different techniques and technologies used to develop frameworks to detect learning styles and to provide adaptivity. Therefore, it can be concluded that more research is needed to fully realize the potential of adaptive e-learning systems based on Felder and Silverman learning styles model, both for proposing novel learning style prediction models and developing new adaptive e-learning systems.

Key words: E-Learning, Adaptivity, Learning Styles Models, Felder and Silverman learning styles model, Artificial Intelligence

1. Introduction

Adaptive e-learning systems try to provide personalized services to the learners. It doesn't matter whether they try to detect and model individual differences of learners or aim to adapt the learning materials to the needs of different learners, learners are always at the center of the design process of adaptive e-learning systems. This view is also supported by studies emphasizing the importance of user modeling [1-3].

Several properties of learners can be modeled for adaptivity purposes to provide information about their preferences and the way they learn [1, 2]. These properties are referred as personalization parameters and some of the widely used personalization parameters can be listed as learner’s level of knowledge, motivational level, learning styles models, media preference and navigation preference [4].

Learning style models can be defined as “the characteristic cognitive, affective and physiological behaviors that serve as relatively stable indicators of how learners perceive, interact with and

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respond to the learning environment" [5]. Learning styles models are quite commonly exploited for modeling learners. As of 2004, 71 different learning styles models have been identified in the literature by [6]. Felder and Silverman learning styles model [7], Kolb's Experiential Learning Theory [8] and Honey and Mumford learning styles model [9] are the most popular models. However, Felder and Silverman learning styles model is selected to be investigated in this paper. The reasons for the selection of this learning styles model are discussed in Section 2, as well as the details of how it models the learning process of learners.

If we look from a more technical side to the technologies and techniques used for modeling learners, there are numerous user modeling approaches that can be used for adaptivity in e-learning systems. Some of the most commonly used techniques are overlay modeling, perturbation models, stereotypes, cognitive theories, machine learning techniques, and semantic web technologies [1-3]. Depending on the techniques incorporated in system design, specific functionalities provided by the system and the context they have been used, adaptive e-learning systems may have different names like adaptive hypermedia systems, intelligent tutoring systems, individualized learning environments and personalized e-learning systems [10, 11].

The rest of the paper is organized as follows: Felder and Silverman learning styles model is examined in Section 2. Section 3 presents an analysis of the adaptive e-learning systems based on Felder and Silverman learning styles model. Section 4 concludes the paper with a brief summary and discussion of future work directions.

2. Felder and Silverman Learning Styles Model

Felder and Silverman learning styles model has four dimensions, where each dimension expresses a different aspect of learning with a linguistic variable. These dimensions can be explained as follows;

- According to the way the learners perceive information, they may be modeled as "sensing" or "intuitive" learners.
- Learners can be modeled as "visual" or "verbal" based on the way they receive information.
- Learners may be distinguished as "active" or "reflective" according to the way they process information.
- Learners can be modeled as "sequential" or "global" based on the way they understand information.

Felder and Silverman learning styles model can be expressed as a Cartesian product of the incorporated dimensions. For instance, a learner may be intuitive, verbal, active and sequential, while another learner can be sensing, verbal, reflective and sequential. To sum it up, this model represents each learner according to their tendencies by classifying them into one of the two poles at each dimension.

In order to have their learning styles information for Felder and Silverman learning styles model, learners should take a scale called Index of Learning Styles (ILS) [12]. The ILS scale contains 11 questions for each dimension, thus, it has 44 questions in total. The questions provide two options to the learners, as a and b. The a and b answers are graded with +1 and -1, respectively. As a result of this, the learning style information can be expressed as an odd number in the interval [-11,+11] at each dimension. The results at each dimension can be viewed in three groups as explained below:

- If a learner's score at a dimension is in the interval [5, 11], then the learner has a stronger tendency for sensing, visual, active or sequential dimension.
- If a learner’s score at a dimension is in the interval [-11, -5], then the learner has a stronger tendency for intuitive, verbal, reflective or global dimension.
- If a learner's score at a dimension is in the interval [-3, 3], then the learner has a balanced learning style in that dimension.

The decision to use Felder and Silverman learning styles model as the basis of this paper is based on the factors listed below:

- Felder and Silverman learning styles model is designed especially for engineering students [7, 13].
- The validity and reliability studies of the Index of Learning Styles (ILS) scale used for Felder and Silverman learning styles model are already in a mature state as analyized by [13].
- Felder and Silverman learning styles model is suggested as the most suitable model for adaptive e-learning systems to provide learning styles based adaptation [14].
- Recent analysis of adaptive e-learning systems accommodating learning styles by [11], [15] and [16] reveal that Felder and Silverman learning styles model is the most commonly used model in the literature. Table 1 presents information from different literature reviews regarding the usage ratio of Felder and Silverman learning styles model over total number of studies exploiting learning styles models in a given year interval. Even though the ratios may vary depending on the aspects each literature review focuses on, Felder and Silverman learning styles model is by far the most widely used model detected in all studies.

Table 1. The usage ratio of Felder and Silverman learning styles model over total number of studies exploiting learning styles models for adaptive e-learning

Reference	Year Interval	The ratio of studies based on Felder and Silverman Learning Styles Model over total number of studies investigated
[11]	2000-2011	35 of 70 studies (% 50)
[15]	2004-2014	36 of 51 studies (% 70.6)
[16]	2005-2014	29 of 69 studies (% 42)

3. Adaptivity based on Felder and Silverman Learning Styles Model

Adaptivity in e-learning systems is usually supported by two main components; learner modeling and learning materials modeling. Learning styles models are one of the core elements used for learner modeling, while SCORM (Sharable Content Object Reference Model) [17] and IEEE

LOM (Learning Object Metadata) [18] are the most commonly used standards for modeling learning materials as learning objects to increase reusability and for metadata modeling of learning objects, respectively. In this regard, the relationship between learning styles models and learning objects for adaptive e-learning has been discussed in detail by [19] with the focus being on Felder and Silverman learning styles model since it is the most commonly used learning styles model and IEEE LOM as it is the most widely adapted learning object metadata definition standard.

Adaptive e-learning systems can be categorized and viewed from different perspectives. These perspectives can provide useful classifications to shed light on the current state of the art in the field and to identify possible future research directions. In this context, several categorizations of adaptive e-learning systems based on different perspectives are discussed in the following part of this section.

Various user modeling approaches can be used to provide adaptivity in e-learning systems. The most widely used techniques such as overlay modeling, stereotypes, perturbation models, machine learning techniques, cognitive theories, constraint based modeling, fuzzy logic based modeling, Bayesian networks and ontological modeling are examined in detail with systems exploiting each technique as a literature review by [3]. It has been discussed that overlay and perturbation models have been losing their popularity in recent years, while fuzzy logic and Bayesian networks have been gaining more interest because of their ability to deal with the uncertainty of learning and learner diagnosis processes. Ontological modeling has also gained more interest in recent years, because of its ability to provide more abstract representations of learner models, which increase the reusability of proposed models [3].

Kardan et al. 2015 presents a content analysis of adaptive e-learning systems from a technical perspective and provides a classification framework for adaptive e-learning systems with two main categories; one based on the adaptive techniques e-learning systems incorporate and the other one with respect to the application field of the adaptive systems [20]. According to the adaptive techniques they use, adaptive e-learning systems are classified into five groups; machine learning & soft computing, semantic web & ontology, application software, hybrid techniques and innovative techniques. From the second perspective, adaptive e-learning systems are categorized based on their application field in seven groups; concept maps construction, learning style detection, learner's problem alleviation, presentation, navigation, multi-dimensional support and the others.

The distribution of papers by the adaptive technologies they incorporate reveal that the most commonly used technology is machine learning and soft computing techniques with 98 of the 190 investigated systems exploiting them. 34 studies use semantic web and ontologies, 30 studies use application software, 21 studies use innovative techniques and 7 studies use hybrid techniques [20].

The distribution of papers by the application field show that the most widely investigated application fields are learner's problem alleviation with 50 papers and presentation with 49 papers. 33 studies are applied for learning style detection, 25 studies adapt their navigation, 16 studies use multi-dimensional support, 10 studies use concept map construction and 7 studies are applied on other fields [20].

However, the distribution of these studies over the years should also be checked to determine the recent trends in adaptive technologies and application fields. When the distribution of papers over the years is checked based on the adaptive technologies they incorporate, it has been observed that there is a decline at application software usage, while machine learning and soft computing techniques are relatively stable over the years and there is an increase at the usage of relatively new technologies such as semantic web and ontologies, innovative techniques, and hybrid techniques. At the second category, the application fields of the studies over the years are checked. The findings show that the studies applied for adaptivity of presentation and learning styles detection have peaked around 2009 and the number of studies in these application fields have been slightly decreasing. Learners' alleviation problem, which is the most popular application field with 50 studies, is still maintaining its popularity.

Learning styles models based e-learning systems have been examined and classified with different perspectives by [11] and [16]. The classification in [11] is performed based on main focus, purpose, study nature, variables used for adaptivity, learning styles models, student modeling approaches, tools used for modeling, data collection tools, research settings and participants of different studies. A similar approach is followed by [16] to classify research studies by their purpose, study nature, methodologies, student modeling approaches, subject/field, participants, data collection tools, learning styles models and summary of the findings. Moreover, [16] also presents a summary of the current research articles from Turkey and discusses the position of the national studies in the field with respect to the international studies in the literature.

Student modeling approaches are classified in two categories as static and dynamic [11, 16]. Static student modeling uses learning styles scales to determine learning styles of learners when they start using the e-learning system and learning styles of learners are considered to remain the same later on. On the other hand, dynamic student modeling does not use scales for learning style detection. Instead, they rely on artificial intelligence techniques to predict learning styles by observing users interaction with the system such as their navigation and content preferences. An important advantage of dynamic user modeling is that it is suitable for modeling the dynamically changing nature of learners needs, characteristics and preferences.

Some of the studies employing dynamic student modeling propose models to predict learning styles of learners [21-24], while some of them propose new models and frameworks to provide adaptivity [25-27]. Dynamic student modeling is applied in 21 of the 69 investigated systems (%30.4) in [16] and 28 of the 70 investigated systems (%40) in [11]. Hence, it can be concluded that dynamic student modeling is an active research area that can attract more researchers to the field in the future.

Adaptive e-learning systems can be categorized according to different perspectives. For instance, categorization can be based on the main purposes and functionalities of the systems, as well as the student modeling approach they incorporate. The integration of learning styles models into adaptive e-learning systems is divided into three main categories by [15]: learning styles detection/prediction using online data (or the online learning styles classification models); the application of learning styles models into adaptive e-learning systems (personalizing learning materials and learning contents); and developing educational games. Research studies [21], [22], [23], [24] and [28] are examples for the first group with learning styles detection/prediction model proposals, while [25], [26], [27] and [29] are examples for the second group that apply learning styles models into adaptive e-learning systems. [30] can be given as an example for the third category that contains educational games.

In order to predict learning styles for the first group of studies, there are several sources that can be used to provide useful data. These potential sources of data are categorized in three groups by [15] as; log files, users' history and background data, and other personalization sources. Each of these data sources provide attributes that can be used for adaptation. These three data sources and the attributes they provide for adaptivity can be explained as given below:

- Log files: The log files collect information about the learners' interaction with the system and the data attributes in log files represent a wide variety of aspects about the learners. Some of the most commonly used interaction data in log files are types of objects chosen, the number of visits, time spent and performance on certain activities, sequences of actions and selected search terms. There are also other activities that can be tracked including searching, taking online exams, quizzes, puzzles, self-assessment tests, playing games, using forums, mails and discussion boards, and reading and downloading materials [15].
- Users' history and background data: This data source group contains static information about learners like gender, education majors, ethnicity and culture. This group may have an important role for learning styles detection, however, it is not used commonly for automatic classification of learners.
- Other personalization sources: This group of data sources includes background knowledge, intelligent capability, cognitive traits (working memory capacity, processing speed, learning stills, reasoning ability), study goals, language and motivation level that can be used alongside learning styles models [15]. This type of data sources are referred as personalization parameters by [4].

These data sources contain potential attributes and behaviors that can be used for adaptivity. However, the studies incorporating them can use different attributes, even if they use similar or the same learning styles frameworks. For example, [24] and [28] use different data attributes even though they both want to identify learners' learning styles by using Felder and Silverman learning styles model. [24] uses data attributes like forums, chats and exam revisions, whereas [28] follows a rule-based approach and uses data attributes with assessment purposes such as performance on a given test, time spent on different type of questions and time spent to check questions.

Even though several data sources and attributes have been used in these studies for learning styles prediction, there is no study so far that compares the contribution of different data sources and attributes to the prediction of learning styles [15]. These type of studies can be beneficial to develop more efficient learning styles prediction models and tools. Hence, this is an important open research area.

Adaptive e-learning systems have been examined based on their application fields, student modeling types, data sources and attributes used for adaptivity, and user modeling approaches and adaptive techniques. Table 2 presents a comparison of recent studies in the learning styles models based adaptive e-learning field based on their functionality, the learner modeling approach incorporated and the techniques and technologies used for providing their functionality in an adaptive way.

Table 2. Comparison of adaptive e-learning systems based on learning styles models

Reference	Functionality	Learner Modeling Approach	Techniques and Technologies Used for Adaptivity
[21]	Learning Style Prediction	Dynamic	Bayesian Networks
[22]	Learning Style Prediction	Dynamic	k-Nearest Neighbor (k-NN) and Genetic Algorithms (GA)
[23]	Learning Style Prediction	Dynamic	NBTree (Naive Bayes and Decision Tree)
[24]	Learning Style Prediction	Dynamic	Bayesian Networks
[25]	Teaching Strategy Personalization	Dynamic	Bayesian Networks
[26]	Learning Object Personalization	Dynamic	Item Response Theory (IRT) and Artificial Neural Network (ANN)
[27]	Learning Object & Learning Method Recommendation	Dynamic	Ontologies
[28]	Learning Style Prediction	Static	Rule (Literature) Based
[29]	Personalization Approach Proposal	Static	Rule (Literature) Based

The analysis of studies in Table 2 show that learning styles prediction/detection is a popular research field as 5 of the 9 studies in Table 2 have this functionality. 4 of these 5 studies use dynamic learner modeling approach for learning style prediction. Studies that aim to provide learning styles based adaptivity may have different functionalities, however most of them also use the dynamic learner modeling approach. Even though the two studies using static learner modeling approach in Table 2 have different functionalities, they both follow a rule (literature) based approach. The studies using dynamic learner modeling approach mostly exploit artificial intelligence techniques such as Bayesian networks, k-nearest neighbor algorithm, genetic algorithms, decision trees and neural networks, while one study uses ontologies.

4. Discussion and Conclusion

In this paper, Felder and Silverman learning styles model based adaptive e-learning systems are examined with different perspectives like the user modeling approaches followed, the adaptive technologies exploited, the application fields applied on, the functionalities targeted and the data sources and attributes used. Two main research areas have been observed; the first area targets design and development of models and tools for learning styles prediction/detection, while the second area deals with the application of learning styles models to provide adaptivity in e-learning systems. The data sources and attributes that can be used for adaptivity purposes in adaptive e-learning systems have been investigated and log files, users' history and background data, and other personalization sources have been detected as the data sources used in the literature. Moreover, the attributes that are used in each data source have been discussed as well.

Learning styles models provide guidelines to e-learning system designers and developers as the behaviours of learners during the learning processes are monitored and how the users learn is tried to be modeled. However, this process has a very complex nature, as the identification of potential predictors of learning styles is not easy and mostly open to human interpretation [15].

Different studies examined in this paper use different data sources and attributes to predict learning styles, but there aren't any studies in the literature so far that propose evaluation of the attributes used for learning styles prediction. Therefore, one of the most important research questions that needs to be tackled in future studies is the comparison of the contribution and performance of different attributes in learning styles prediction.

Another significant research area involves the techniques and technologies used for developing models and tools to detect learning styles. Bayesian networks is the most popular technique used for prediction of learning styles [21, 24]. However, more research that compares and combines different approaches and techniques can be fruitful to achieve better results both for learning styles prediction model and tool developers, and adaptive e-learning system developers [15, 16].

Using different learning styles models together can provide better results for adaptivity. In this context, Felder and Silverman learning styles model and Kolb’s experiential learning theory, which are closely related to each other, can be integrated in future studies. Thus, combining different learning styles models is another research area that needs to be tackled in the future. Another future work direction can be development of new techniques for more efficient processing of system logs to offer better adaptivity features in e-learning systems.

Finally, the interdisciplinary nature of the e-learning field needs to be emphasized. Teachers, students, educational technology scientists, curriculum developers, computer and software engineers should all work together as stakeholders to develop more efficient adaptive e-learning systems.

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