SEMANTIC MODELLING FOR LEARNING STYLES AND LEARNING MATERIAL IN AN E-LEARNING ENVIRONMENT

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ABSTRACT

Various learners with various requirements have led to the raise of a crucial concern in the area of e-learning. A new technology for propagating learning to learners worldwide, has led to an evolution in the e-learning industry that takes into account all the requirements of the learning process. In spite of the wide growing, the e-learning technology is still lacking the ability to achieve the best personalised learning path for each learner resulting in performance dissatisfaction. Recent research indicates that each learner has a unique way of learning that leads to different preferences in the selection of the learning resources. Thus, the learning material must be tailored for the individual learners in order to meet their own personal needs. In this paper, we present a novel approach for designing a model for an adaptive e-learning course and learning styles based on ontology and semantic web technologies. In this approach, we build an adaptive student profile through analysing the pattern of the learner's behaviour while using the e-learning course in accordance to the Felder- Silverman learning style model (FSLSM).

KEYWORDS

E-learning; Semantic Web; Personalisation; Adaptive System; Learning Style; FSLSM

1. INTRODUCTION

E-learning industry has created vast and growing revolution due to many advantages such as scalability, simplicity and access flexibility. Technology enhanced learning currently trends to focus on the significant concern of learning in terms of cognitive processing. In addition, recent research endorses the necessity of the content relevance for each learner. Therefore, customising the content and context of the information has to be attained for each learner in an exciting, easy and creative way.

The main issue of e-learning courses is the scarcity of personalisation that can be defined as the ability of the learning process to get customised and tailored according to the learners' preferences and characteristics (Chen, Lee & Chen, 2005). The personalisation process covers the learning objectives, the content and the learning method. While demonstrating the significance and the effectiveness of adaptive systems, researchers regularly emphasise the importance of personalisation after taking into account the user performance, cognitive style, knowledge level, or learning style in order to determine the most suitable learning path (Montazer & Ghorbani, 2011). In a fully personalised e-learning environment, the learning objectives and content, as well as the method and pace, may vary (Keefe, 1991). The idea of an adaptive system is to provide contents to different users based on their individual learning preferences.

According to Brusilovsky (Brusilovsky, 1996), the system has to be able to determine different content paths for the same learners at different times according to their chosen preferences, goals, experiences and knowledge. It is significant that the course content is well customised according to the needs of the individual learners in order to personalise their learning experiences (elkherj & Freund, 2014).

Thus, our approach will focus on the personalisation by enhancing the performance of the personalising procedure in the learning process. This could be achieved by increasing the effectiveness both of monitoring the learner's behaviour to determine the accurate learning style, and filtering the content of the learning material according to a relevant recommendation. In addition, our approach provides recommendations for the appropriate type of knowledge resources by using semantic rules reasoning.

As such, we assume that our model will meet the expectations to achieve an effective personalised system. The aim of our approach is to present a novel semantic model for both the learning material and the learning style. Our model extends the model of previous work (Halimi & Seridi-Bouchelaghem, 2015) by integrating the learning material with comprehensive features, along with structuring the tendencies of the learning style in order to enhance the efficiency of the semantic inference mechanism.

This paper begins with an overview of the related work for both the learning style theories and the approaches for the automatic User Model. The proposed architecture of the ontology model is illustrated next, along with the elaboration of the semantic modelling, and the computational model. Then, an application scenario of learner interaction with the e-learning course is presented. The conclusion will be given in the last section.

2. RELATED WORK

2.1 Learning Style

Definitely, learning style is one of the main factors in personalisation as a cognitive perspective for the learner. According to Keefe, the learning style consists of the modality meter of learning (Keefe, 1991; Bansal, 2013). Coffield et al. (Kanninen, 2008) provide a comprehensive categorisation, shown in TABLE 1, for the existing learning style models, divided into five families according to the related concept of their structure which are learning style preferences, cognitive structure, personality type, steady learning preferences, and other learning strategies and orientations (Coffield, 2004).

Table 1. Coffield comprehensive categorisation of learning style models (Kanninen, 2008)

Author(s)	Assessment tool	Year
Genetic and other constitutionally based learning styles and preferences including the VAKT		
Gregorc	Gregorc Mind Styles Delineator (MSD)	1977
Cognitive structure		
Riding	Cognitive Styles Analysis (CSA)	1991
Stable personality type		
Apter	Motivational Style Profile (MSP)	1998
Myers-Briggs	Myers-Briggs Type Indicator (MBTI)	1962
Flexibility stable learning preferences		
Herrmann	Brain Dominance Instrument (HBDI)	1995
Honey and Mumford	Learning Styles Questionnaire (LSQ)	1982
Felder and Silverman	Index of Learning Styles (ILS)	1996
Kolb	Learning Style Inventory (LSI) LSI Version 3	1979 1999
Learning approaches and strategies		
Sternberg	Thinking Styles	1998

Some of these models were mentioned vastly in the literature (Graf, Kinshuk & Liu, 2008) due to their effectiveness. Like the Myers-Briggs Type indicator (MBTI) from the personality type family that refers to the Carl Jung's theory. This theory divides humans as introverts or extroverts, by sensing or intuition, thinking or feeling, and judging or perceiving.

In the family of learning style preferences, Kolb's experiential theory is displayed within a four stage learning cycle. The stages are: concrete experience, reflective observation, abstract conceptualisation, and active experimentation. Honey and Mumfords' model divides learning styles into activists, theorists, pragmatists, and reflectors. Another model is Pask's model of the Serialist/Holist/Versatilist learning styles (Graf, Kinshuk & Liu, 2008). The Herrmann Whole Brain Model, represents learning styles according to the quadrants of the brain along with their functionalities. From the same family, we have chosen the Felder and Silverman learning style Model (FSLSM) that will be explained in more detail in the following section.

2.1.1 Felder and Silverman Learning Style Model

As shown in Figure 1, our chosen model considers the cognitive science along with the principles of learning and personalisation.

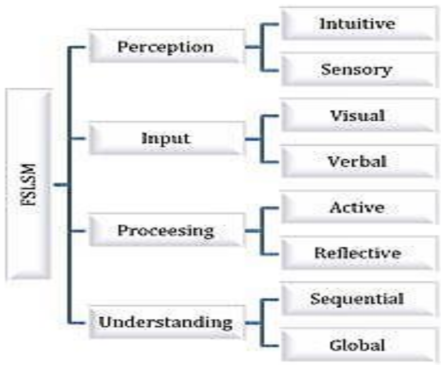

Figure 1. Learning styles of Felder and Silverman learning style model (Felder & Silverman, 1988)

According to the FSLSM, learning styles are classified into four dimensions (Nafea, Maglaras, Siewe, Smith & Janicke, 2016). These dimensions start with the perception, which is the kind of knowledge that the user desires to recognise. Learners may be intuitive when they prefer abstracts or theories. Other learners may be sensory when they prefer examples or practices. The second dimension is the input which is the method of learning the user favour to learn with. Learners may be visual when they prefer images, graphs and flowcharts. Other learners may be verbal when they prefer texts or spoken notations. The third dimension is the processing, which is the way the learner demonstrates learning. Learners may be active when they prefer working with other users. Other learners may be reflective when they prefer thinking and working by themselves. And the fourth dimension is the understanding, which shows the user knowledge development. Learners may be sequential when they prefer learning in continuous minor stages. Other learners may be global when they prefer viewing the end results and the whole picture.

2.1.2 Reasons for choosing FSLSM

We chose the FSLSM as a basis for the adaptive system because of many reasons. It has been approved by various specialists, since it is the most appropriate model for educational systems. It is capable of describing learning style in terms of tendencies and balanced preferences. It is user-friendly and the results are easy to interpret. Furthermore, the FSLSM is comprehensive for many major learning style models, and describes the learning style in more details than other models (Liyanage, Gunawardena & Hirakawa, 2014; Franzoni, Assar, Defude & Rojas, 2008; Darwesh, Rashad & Hamada, 2011).

2.2 Existing Learning Approaches for Automatic User Model

Recent researchers of automatic user modelling have been adopting the new concept of the knowledge-based approach, that is sometimes called literature-based by some researchers. Graf et al. (Graf, kinshuk & Liu, 2008; Graf, 2007) suggested a novel methodology built in LMS Moodle, to collect the appropriate hints related to the user preferences originally from the LMS. The system achieved good precision rate comparing to other approaches. Later, Graf et al.(Graf, kinshuk & Liu, 2009) suggested an automatic modelling with an innovative tool to support it. A similar implementation to the previous was the work of Simsek et al. (Simsek, Atman, lnceoglu & Arikan, 2010) in Moodle LMS, however, they focused on the dimension of processing (active- reflective) and the implementation was able to achieve a rate of accuracy of 79.6%.

Dung et al. (Dung & Florea, 2012) extended the work of Graf et al. (Graf, Kinshuk & Liu, 2008) in addition, they concentrated on the number of visits and their durations. The rate of accuracy was roughly the same as in Graf et al (Graf, Kinshuk & Liu, 2008). Pursuing developing applications, Atman et al. (Atman, Inceoglu & Aslan , 2009) suggested a web-based system that provided a specific label to the modules in order to correlate them to one of the learning styles, achieving 83.15% accuracy for the processing dimension with the use of the formula of Garcia et al. (Gregorc & Ward, 1977). Dung et el. (Dung & Florea, 2013) proposed POLCA in 2013 that focused on tracking the learners' behavior through their interactions with the labeled learning objects.

Recent studies focused on improving personalised learning environments based on describing knowledge using ontologies. Such approach was implemented by Halimi et al. (Halimi & Seridi-Bouchelaghem, 2015) in a social learning environment. It formulated a powerful method that can analyse the behaviour by semantic inferences, identify learning style, and provide better recommendation. The Didaskon Platform (Didaskon & Sound, 2013) was developed by semantic web technologies to automatically arrange a different learning path for each student according to his preferences and characteristics. Another application annotated the learning objects of the content automatically with the use of ontologies (Jovanovic, Gasevic & Devedzic, 2006; Gasevic, Jovanovic, Devedzic & Boskovic, 2005).

Gutierrez et al. (Gutierrez, Pardo & Kloos, 2004) developed an algorithm for monitoring the learner’s activities during the learning process, and constantly adjusting his profile with the use of ontology. The study of Nafea et al. (Nafea, Maglaras, Siewe & Shehab, 2015;Nafea, Maglaras, Siewe, Smith & Janicke, 2016) is about an adaptive LMS that depended on the technology of semantic web and ontologies. Focusing on semantically modelling the user, the framework automatically reviewed the learners’ behavior pattern based on the Myers-Briggs theory and the FSLSM using the Moodle.

3. CREATION OF SEMANTIC MODELLING

The created ontology for an e-learning system, provides a clear illustration of the distribution of the knowledge resources domain. The ontology structure divides the knowledge domain into definite resources like chapters, exercises, and forums. The knowledge resources are extended by behavior pattern substructure of stay, visit, and many trials. Furthermore, each resource is supported with multiple types of media representation such as text, image, and video. Another class, learning style, is constructed according to the FSLSM of four dimensions explained earlier, along with their opponent styles. Lastly, the ontology provides various users such as Tutor, and Student based on their usage and interaction with the system.

The use of ontology benefits the system in several aspects like supporting the knowledge resources with a detailed annotation that leads to sharing and reusing data. The ontology is capable of providing clear definitions for users, knowledge domain resources, and different learning styles. Also, the support of the based on demand knowledge can be efficiently achieved by the ontology, by the inference mechanism and the precise tracking and response of ontology among resources. In addition, the ontology enhances the system effectiveness in getting the proper resources since it minimises the terminology imprecision.

3.1 Proposed Architecture

Recent ontology-based systems for e-learning courses using the semantic web are ready to apprehend hidden semantic associations by exploring the knowledge and structure of the ontological model. By using linked data in the ontology, it becomes easier for the system to interpret data and make good detections or suggestions to users.

In this paper, the proposed architecture for e-learning courses based on Semantic Web, as shown in Figure 2, is to represent the course knowledge domain, and the user profile or the learning style model. It analyses the pattern of the learner’s behavior to establish and update the learning style model, as well as to develop a personalised learning path most suitable for the individual needs. The significance of this system is that individual learners would get a unique learning experience according to their learning styles.

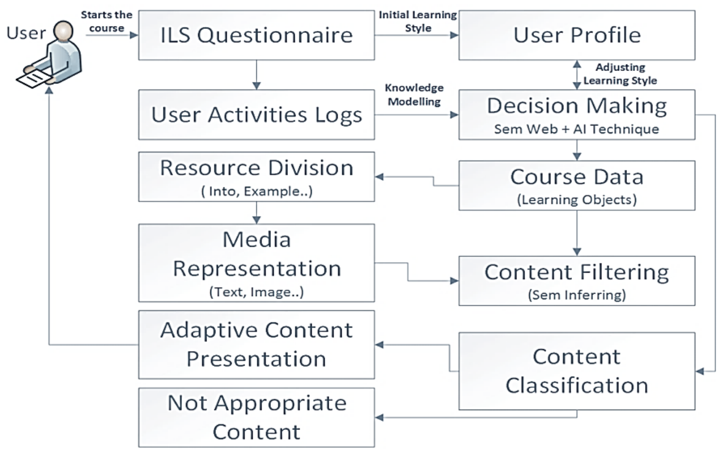

Figure 2. Architecture for personalising the learning material to learning style

The main components of the proposed architecture are:

3.1.1 ILS Questionnaire

It is FSLSM ILS Questionnaire. The answers will be gathered and used to initially model the learner's learning style. And the result will be used later in the evaluation process.

3.1.2 User Activities Logs

They are records of the learner's interactions with the learning material, which includes his behavior, tests results, visit timings and frequencies.

3.1.3 Decision Making

It is the process of analysing the learner's behaviour by the semantic web inference, and the classification of the learning style based on the FSLSM. An AI technique will be added in the future work to this component to support the accuracy of decision making. Consequently, it will be followed by the process of designing the recommended learning content for the learner.

3.1.4 Course Data

It is all the resources of the learning material with the different media presentations.

3.1.5 Content Filtration

It is the process of designing the recommended learning content for the learner.

3.1.6 Content Classification

It is the process of splitting the learning resources into appropriate and not appropriate resources.

3.1.7 Adaptive Content Presentation

It is all the suitable resources for the learning material that construct the adaptive learning path based on the learning style.

3.2 Conceptual Model

The conceptual model for the e-learning course ontology, shown in Figure 3, describes how the learner interaction is demonstrated by the semantic reasoning mechanism to model his learning style, and to recommend the learning material.

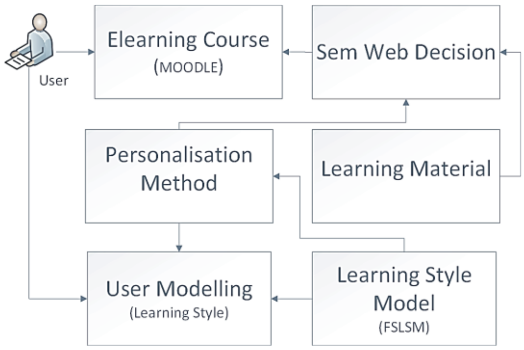

Figure 3. Conceptual model

3.2.1 Moodle platform

Moodle is the learning management system that is used to build the learning course, and allows the student to interact with the learning material.

3.2.2 Learning material

Since it is personalised learning it is crucial to support a variety of representation and media to the learning material in order to fit to the various learning styles. Also, the content is well organised into units to facilitate the path recommendation and distribution. At some level, the learning material will be under the filtration process by the semantic web inferring mechanism to segregate the appropriate resources from the not appropriate, in order to structure the suitable content to the learner.

3.2.3 User Model

The learner's model is the reflection of the information that emerges during the learner's interaction with the system (Nafea, Maglaras, Siewe & Shehab, 2015). The learner's profile will include his personal information, along with his model of learning style and preferences. Interactions history and recommendations are also helpful data that need to be stored.

3.2.4 Learning Style Model

The Felder and Silverman learning style model was chosen in our research to be our criteria to refer to when analysing the behavior and deciding the learning style.

3.2.5 Semantic Web Decision

The semantic web inferring mechanism gives the privilege of sharing and reusing the data which will enhance the efficiency. The Semantic Web is in charge of detecting the learner's behavior in order to infer his learning style. After updating the learner's model, the semantic web will decide how the learning material is filtered to get the useful resources. Moreover, there will be a semantic decision for the recommended path for the learner.

3.3 Computational Model

The e-learning material and the learning style ontologies were constructed in Protégé assistive technology to model various interlinking hierarchies. The schematic structure of the ontology based e-learning course is presented in Figure 4 and Figure 5. It starts when the user enters the e-learning course, and an initial learning style is determined by the results of ILS questionnaire and thus the learner's initial model is developed. The ontology is in charge of detecting and storing the result that indicates a preference of one of the 16 learning styles combinations of FSLSM.

In our approach, the critical features are the knowledge domain resources, the multiple representations for these resources, and the learning styles preferences that match these different resources. These features determine the key concepts of our ontology-based e-learning course.

The ontology describes the domain of knowledge by representing its objects and the relationships between these objects; it allows to formally defining different users and their roles (student, tutor, etc.), resources (courses, tutorials, videos, etc.), learning styles and preferences. It also provides various representations for several objects in the learning content, which means, once the learning style is determined, the nearest proposed type of media, which corresponds to his learning style is recommended. For example, if it is determined that a learner is visual, the video explanation will be provided to him instead of the text or spoken notation.

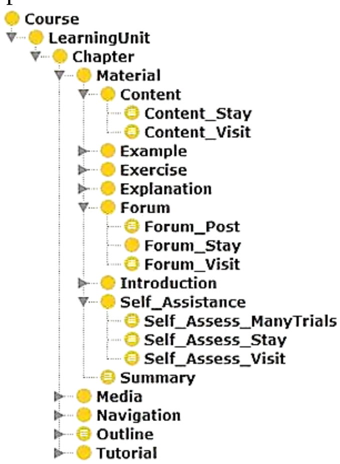

Figure 4. Part of the learning material ontology

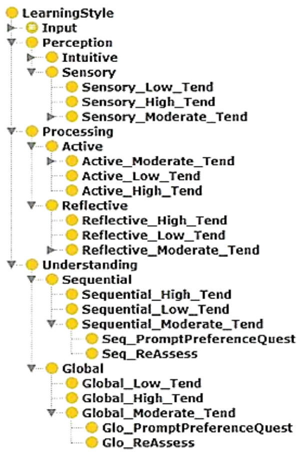

Figure 5. Part of learning style ontology

3.3.1 Basic heuristic of the Ontology Classes

The structured ontology contains many classes which are the course, the learning styles and the user. For the course class, there are subclasses and further divisions such as of the learning units, chapters and as the type of content media.

Moreover, each unit of the learning material is extended with some features that can help the content filtration and the reasoning process to be quicker, and more accurate. An example of a material unite is the forum. The forum unit is supported by several features like the Forum_Post, the Forum_Stay and the Forum_Visit. After monitoring the learner's behavior during a learning the course, these features assist the Semantic decision for the learning style modelling. When the learner is active in posting and asking in Forums, it is an indicator that the learner is of type Active. While if the learner rarely participates, or keeps watching and observing only, then it is an indicator that the learner has a reflective learning style.

The learning styles class is also divided according to the FSLSM. Further divisions describe the four dimensions learning styles into the different learning styles. In turn, each learning style is structured according to the learning preferences that result to the learning material.

For example, one of the learning style dimensions is perception, which is in turn divided into the intuitive and the sensory. The intuitive object is divided into preferences like theories and abstracts, while the sensory is extended with exercises and examples. Also, the learning styles are categorised into style tendencies to help the process measuring and deciding the exact learning style. However, once a style is trivial, or moderate, there are two options to deal with the case as shown in Figure 5, either to send a direct prompt question for the learner's preference for the next content or to focus on the reassessment process.

3.3.2 Phases of Content Personalisation

The personalisation process starts with the determination of the initial learning style of the learner via answering the ILS Questionnaire of FSLSM. Next phase is the semantic modelling decision of learning style that is established for the learner after the interaction with the system, along with the decision of the appropriate content resources from the knowledge domain. Then there is the refinement process by the inferring mechanism of the Semantic Web, which happens by studying the learner characteristics, to set the possible resources that better suit the learner's learning style model.

When two opponent Learning Styles have equal tendencies, the ontology provides some options. The first is to show a direct prompt question to ask the learner about his preference of the next content. Another option is to focus on the reassessment process through his interaction with the content in order to become more accurate in the next decision of his learning style. Both options can be applied for the learner in the same time. Considering, that in some cases the learner may have moderate tendency towards a learning style, the ontology can support him with these options many times to avoid errors. As mentioned above, a technique of artificial intelligence will be added in a later phase to model quantitative and qualitative information of the behavior pattern; however, it is not the focus of this paper.

Finally, after updating the learner model, a division process is conducted on the content material, to separate the needed appropriate from the not appropriate content resources. Learner characteristics are examined, to set the possible resources that better suit the learner's learning style model.

4. APPLICATION SCENARIO

In this section, we will elaborate on the scenario for the learning styles of the input dimension of the FSLSM. When a learner first enters the course, he will fill in the ILS Questionnaire to initially model his learning style. Assuming that the result of the questionnaire determines that he is verbal, which would mean he likes to receive the knowledge from texts, or spoken notations.

After interacting with the course content, his behavior including the number of visits for each item in the content, the time spent on each item and the frequencies will all be monitored. The ontology built for the learning course does the reasoning and evaluates the results. By the semantic referencing mechanism the learner will be assigned to the learning style. Below is an ontograf presentation for the Input learning style in Figure 6.

Once the evaluation resulted in reaching a threshold percentage of usage and interaction with a specific type of items, the ontology will infer his learning style. This learner could have answered the ILS

Questionnaire randomly, or he could have had a misconception about his preferences. When his behavior shows that he prefers focusing on videos, graphs, and images rather than the text and spoken notes, the semantic decision will model him as a visual learner, his profile will be updated, and the learning material will be filtered in order to be presented with the recommendation according to his learning style.

In case the learner is indifferent in learning from texts images or videos, that has a moderate tendency towards verbal or visual styles, a couple of direct prompt messages in the learning chapter will be shown to ask him “Would you Like the next section to be an article or video?”, that will help in the behavior monitoring and the learning style modelling. With further collaboration and interaction with the learning course, the ontology keeps refining his learning style model and adjusting the recommended learning path for the learner.

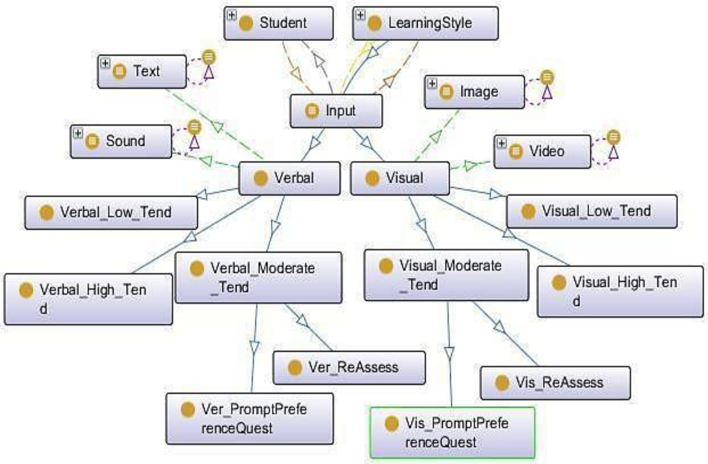

Figure 6. Ontograf presentation of the inputlearning style

5. CONCLUSION

A revolutionary change is emerging to enjoy the privileges of the technology and the Semantic Web to serve the creating of an operative e-learning courses system, capable of determining the learning style and providing the most appropriate learning path accordingly.

Our approach provides a model for an adaptive ontology-based e-learning environment that has the advantage of semantic inference mechanism to link the behavior of learners to their learning styles and, then, to the appropriate knowledge resources. This model is being implemented and will be used in the next piece of study. The approach is distinctive in embedding the personalised ontology of e-learning courses with many details of the different media representations of the existing knowledge resources that facilitate the selection amongst them in order to meet the needs of each learning style.

Furthermore, the structure of the learning material includes some new features such as visits and number of trials to induce higher levels of semantic reasoning mechanism, in less time, and definitely more accurate. Moreover, the learning style ontology structure includes some new features like the styles tendencies. The e-learning course ontology was constructed according to the criterion of the Felder and Silverman learning Style Model that provides eight different learning styles categorised into four dimensions, which are the perception, the input, the processing, and the understanding.

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