Interaction Design and Architecture(s) Journal - IxD&A, N. 9-10, 2010, pp. 65-84

Selection of Appropriate E-learning Personalization Strategies from Ontological Perspectives *[1]

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Abstract. When there are several personalization strategies of E-learning, authors of courses need to be supported for deciding which strategy will be applied for personalizing each course. In fact, the time, the efforts and the learning objects needed for preparing personalized learning scenarios depend on the personalization strategy to be applied. This paper presents an approach for selecting personalization strategies according to the feasibility of generating personalized learning scenarios with minimal intervention of the author. Several metrics are proposed for putting in order and selecting useful personalization strategies. The calculus of these metrics is automated based on the analyses of the LOM (Learning Object Metadata) standard according to the semantic relations between data elements and learners' characteristics represented in the Ontology for Selection of Personalization Strategies (OSPS).

Keywords: Ontology, personalization strategies, metadata.

1 Introduction

The personalization of learning scenarios aims at adapting the presentation of learning objects to a set of learners' characteristics. This adaptation has the promise to motivate learners and compress the time needed to achieve their objectives. In fact, learners find rapidly the searched knowledge in the form they can understand easily when the learning scenarios are generated according to their characteristics like their

[1] This paper is an extension of the work presented in [1].

level of knowledge, learning styles, cognitive traits, preferences and so on. However, considering all learners' characteristics could be constrained by two limits. First, the course must contain a lot of different learning objects for suiting any sets of learners' characteristics. Typically, in order to fulfill this constraint, a teacher needs to spend a lot of time and effort on extending his/her course with additional learning objects which represent the learning material in different ways, for learners with different characteristics. Second, learners have to respond to many questionnaires for determining all characteristics which is a time consuming and fastidious task [2]. An operational solution consists of selecting a subset of complementary[2] learners' characteristics which are considered by the learning objects that are already included in the course. In this way, the first constraint is satisfied and the course will contain the necessary learning objects for personalizing it. In addition, the second constraint is lightened given that only a subset of characteristics will be considered and learners have to respond only to the questionnaires of the specified characteristics. In this paper, we present an approach for recommending personalization strategies based on the learning objects included in the course as well as on how well they support particular learners' characteristics. This approach is automated based on the LOM standard [3] and an ontology for selection of personalization strategies. The approach can additionally generate personalized learning scenarios. For clear description of the approach, the technical terms used in the paper are defined. These terms are:

- Personalization parameter: A set of learners' characteristic such as learning styles or learners' level of knowledge.
- Personalization strategy: Selected personalization parameters.
- Learning scenario: A set of learning objects useful for learning the concepts of the course.
- Boolean logic: A reasoning mechanism which considers two values for reasoning: true and false. These two values could be represented respectively by 1 and 0.
- Fuzzy logic: A reasoning mechanism which considers an infinite number of values for reasoning. These values belong to the interval [0…1].

This paper is structured as follows. Section 2 presents related works which focus on personalization based on knowledge sharing with ontologies. Section 3 presents the Ontology for Selection of Personalization Strategies (OSPS) which is an ontology representing the semantic relation between data elements of LOM standard and learners' characteristics. Section 4 explains the approach by a short example. Section 5 presents an evaluation of the proposed approach. Finally, section 6 concludes the paper with a summary of the work and futures perspectives.

[2] A set of complementary learners' characteristics includes the opposite characteristics for already included characteristics. For example, by considering the learners characteristic "verbal" of the Felder-Silverman learning style model, the opposite characteristic "visual" has to be considered too.

2 Related Works

Ontology is one of the important solutions for sharing knowledge and reasoning about it. In particular, many works have shown the promising benefits of using ontologies for personalizing E-learning and search for documents. An important set of these works use domain ontologies for an extensible representation of knowledge about specific domains. For example, Wang and Hsu [4] defined an approach to support retrieval of teaching templates and learning objects based on a course ontology and a content ontology. The course ontology describes the term relation among course topics and the content ontology describes the relations among learning objects. Zeng et al. [5], like Wang and Hsu [4], have used a course ontology too. They (Zeng et al.) presented two approaches for capturing the seeking information based on a course ontology and the navigation history. The first approach focuses on the question-answering process. The second one focuses more on the classification of the e-documents read by each user. While some works start from ontologies specifying courses knowledge, other works are based on pedagogical knowledge from instructional perspective. For example, Sancho, Martínez and Fernández-Manjón [6] defined an approach for the personalization of courses according to the learner level of knowledge, the learning goal and the Felder-Silverman learning style model. To do this, authors' work was based on a domain ontology to share knowledge on a specific domain and a pedagogical ontology to provide a description of a learning resource from an instructional perspective. Henze et al. [7] defined an approach for personalizing learning resources (according to the learner performance and interaction with the system) based on domain, user and observation ontologies. The domain ontology is used to describe the document space, relations of documents and concepts covered in the domain of this document space. The user ontology describes the learner characteristics. The observation ontology models different possible interactions of a user with the hypertext. Kontopoulos et al. [8] proposed an approach for course planning according to learners' goals and their level of knowledge, using a domain ontology. Chi [9] presented an approach for curriculum sequencing according to the learners' goal, using a domain ontology, which specifies the curriculum sequencing knowledge. Isotani et al. [10] proposed a method for group formation, according to individual and group goals, based on a collaborative learning ontology, which represents relationships between group formation and interactions between individuals. Other works focus on domain ontologies for capturing the user interests like the works of Jiang and Tan [11], and Weng and Chang's work [12]. Jiang and Tan [11] present a set of statistical methods for the selection of domain ontology part which focus on individual user interest. Weng and Chang's work [12] is based on a domain ontology, which classifies academic research papers and the navigation of users to determine their individual interests. In addition, domains ontologies are used for students' assessment in the works of Gladun et al. [13], and Žitko et al. [14]. Gladun et al. [13] presented an approach to control students' acquired knowledge based on an algorithm for comparing a reference ontology defined by the teacher with ontologies proposed by students. Žitko et al. [14] specified an approach for generating multiple choice questions based on an ontology, which describes specific domain knowledge. Besides the works on ontology specifying courses, pedagogical approaches, and learners knowledge, some works focus on links of documents annotation with ontologies. For example, Eriksson [15] proposed an approach for linking documents to ontologies based on document annotations. Lu and Hsieh [16] presented an extension for SCORM CAM based on the relationships between learning topics and learning objects as well as between learning objects. Hsu et al. [17] presented an approach for hybrid conversion of markup documents into a desired XML format based on three ontologies, namely transcoding Web service annotation ontology, client device annotation ontology, and markup language taxonomy ontology.

In summary, while many works use ontologies for the personalization of E-learning and search of documents, the usage of ontologies for the selection of appropriate personalization strategy has not been explored so far except the short version of this work [1]. An ontology useful for this kind of selection should represent the knowledge necessary for measuring the effectiveness of personalization parameters when used for personalizing a given course. As an indicator for this effectiveness, this work presents the average of learners groups which could beneficiate from personalization when using a set of personalization parameters for the given course. This paper presents an ontology which could be used to select the appropriate personalization strategy for each course. The proposed ontology is based on the semantic relations between data elements of LOM standard and learners' characteristics.

3 Ontology for Selection of Personalization Strategies (OSPS)

Given the semantic relations between data elements of LOM standard and learners' characteristics, the automatic selection of significant personalization strategies becomes feasible and operational. Currently, OSPS represents semantic relations between data elements of LOM standard [3] and learners' characteristics. Concerning data elements, they constitute groups of data on the learning objects. A data element is represented by a name combined with a number for referencing it (Sometime, the name of data element is insufficient to reference the data element especially when two data elements have the same name. For example, the data element *3.4 Language*, which refers to the language of this metadata instance, and the data element *5.11 Language*, which refers to the human language used by the typical intended user of this learning object, have the same name.). In addition, a data element may have a list of possible values. Data elements considered in the ontology are:

- 5.1 Interactivity Type: Predominant mode of learning supported by this learning object. Its possible values considered in OSPS are active and expositive. An active learning object prompts the learner for semantically meaningful input or for some other kind of productive action or decision. An expositive learning object displays information but does not prompt the learner for any semantically meaningful input.
- 5.3 Interactivity Level: The degree of interactivity characterizing this learning object. Interactivity in this context refers to the degree to which the learner can influence the aspect or behavior of the learning object. The values considered in OSPS are very low, low, medium, high, and very high.

For example, Learning objects with Interactivity Type = "active" may have a high interactivity level.

- 5.2 Learning Resource Type: Specific kind of learning object. The values considered in OSPS are simulation, diagram, figure, graph, narrative text, and lecture.
- 4.1 Format: Technical data type(s) of (all the components of) this learning object. The values considered in OSPS are video, audio, image, text, application, and example.
- 5.11 Language: The human language used by the typical intended user of this learning object. The values considered in OSPS are: en for English, and de for German.
- 1.7 Structure: Underlying organizational structure of this learning object. The values considered in OSPS are linear and hierarchical. Linear structure describes a learning object composed of fully ordered component. Hierarchical structure describes a learning object composed of parts whose relationships can be represented by a tree structure.
- 5.8 Difficulty: How hard it is to work with or through this learning object for the typical intended target audience. The values considered in OSPS are very easy, easy, medium, difficult, and very difficult.
- 5.4 Semantic Density: The degree of conciseness of a learning object. The semantic density of a learning object may be estimated in terms of its size and span. The values considered in OSPS are very low, low, medium, high, and very high. An example for low semantic density would be a screen filled up with explanatory text, a picture of a software interpreter, and a single button labelled "Click here to continue". On the other hand, an example for high semantic density would be a screen with only little text, the same picture, and three buttons labelled "input language", "output language", and "detailed components".
- 9.1 Purpose: The purpose of classifying this learning object. The values considered in OSPS are educational objective and competency.

Concerning learners' characteristics, they are grouped in personalization parameters. The diversity of personalization parameters constitutes a richness of OSPS and offers different alternatives for teachers about the personalization of their courses. Actually, OSPS includes the following personalization parameters:

- Active/Reflective dimension of the Felder-Silverman Learning Style Model: is a personalization parameter proposed by Felder and Silverman [18]. It includes the learners' characteristics active and reflective. Active learners tend to retain and understand information best by doing something active with it such as discussing or applying it or explaining it to others. Reflective learners prefer to think about it quietly first [19].
- Visual/Verbal dimension of the Felder-Silverman Learning Style Model: is a personalization parameter proposed by Felder and Silverman [18]. It includes the learners' characteristics visual and verbal. Visual learners remember best what they see such as pictures, diagrams, flow charts, time lines, films, and demonstrations. Verbal learners get more out of words such as written and spoken explanations [19].
- Sequential/Global dimension of the Felder-Silverman Learning Style Model: is a personalization parameter proposed by Felder and Silverman [18]. It

includes the learners' characteristics sequential and global. Sequential learners tend to gain understanding in linear steps, with each step following logically from the previous one. Global learners tend to learn in large jumps, absorbing material almost randomly without seeing connections, and then suddenly "getting it." [19].

- Honey–Mumford learning style. Honey and Mumford [20] identified four styles of learning (Activist, Reflector, Theorist, and Pragmatist), which have much in common with Kolb's work [21] and have strong correlations with the learning cycle.
- Media Preference: enables the learner to be provided with the form of learning objects he/she prefers most, including text/image, sound, video, and simulation.
- Navigation preference allows the navigation in the learning material in the learner's preferred order, distinguishing between breadth-first and depth-first.
- Learner's level of knowledge: is used for taking into account the learner background when communicating learning objects to the learner. This personalization parameter includes the learners' characteristics beginner, intermediate, and advanced.
- Motivation level. Keller [22] cited in Small [23] defined the ARCS model which identifies four essential components for motivating instruction (Attention, Relevance, Confidence, and Satisfaction). This personalization parameter includes the learners' characteristics low, moderate, and high.
- Language preference allows the presentation of learning objects in the learner's preferred language (e.g., English, German).
- Pedagogical approach. Essalmi, Jemni Ben Ayed, and Jemni [24] introduced the pedagogical approach as a personalization parameter. The learners characteristics considered in OSPS are objectivist approach and competency based approach.

Table 1 presents 76 relations between data elements and learners' characteristics. The table contains 3 main columns: data elements extracted from LOM standard, learners' characteristics, and the degrees which associate data elements with learners' characteristics. These relations are used for the selection of personalization parameters. Column 1 is divided in two sub-columns for presenting the couple of metadata names prefixed by their reference numbers and metadata values. Column 2 is also divided in two sub-columns for presenting the learners' characteristics in the form of linguistic terms as well as the personalization parameters which include them.

As an example of semantic relations represented in Table 1, the value *active* of the data element *interactivity type* is correlated with the learner characteristic *active* of the *Felder-Silverman learning style model*. Furthermore, when the value of the data element *interactivity level* is *high*, the coincidence degree with the learners' characteristic *active* is *high* (100% in the column 3). In fact, there are 5 ranged (putted in order) values included in the data element *interactivity level*: *very low*, *low*, *medium*, *high*, and *very high, which could be* associated respectively with the 5 ranged degrees (which associate the values of the data element *interactivity level* with the learners' characteristics *active* of the *Felder-Silverman learning style model*) 20%, 40%, 60%, 80%, and 100%. The degree increases when the value of the data element interactivity level increases. In addition, successive degrees are eloigned by an equilibrate distance (40% - 20% = 60% - 40% = 80% – 60% = 100% - 80%). As another example, the *interactivity type expositive* is correlated with the *Felder-Silverman learning style reflective*. The degree of this correlation depends also on the *interactivity level*. In particular, the degree is *high* when the *interactivity level* is *high* and *low* when the *interactivity level* is *low*. Similarly to the *Felder-Silverman learning styles active* and *reflective*, the *Honey-Mumford learning styles activist* and *reflector* are associated with the data elements *interactivity type* and *interactivity level*. Furthermore, the *Felder-Silverman learning styles visual* and *verbal* are correlated with the data element *learning resource type*. In particular, a learning resource type like *diagram*, *figure* or *graph* is associated with the learning style *visual* while a learning resource type like *narrative text* or *lecture* is associated with the learning style *verbal*. These associations between values of the data element *learning resource type* and some learners' characteristics have the same degree: 100%. In fact, the data element *learning resource type* does not include a set of ranged values. There are others associations between data elements and learners' characteristics. For example, the *Felder-Silverman learning style sequential* is associated with the value *linear* of the data element *structure*, and the learning style *global* is associated with the value *hierarchical* of the same data element (The associations between values of the data element *structure* and some learners' characteristics have the same degree: 100%. In fact, the data element *structure* does not include a set of ranged values.). Similarly to the *Felder-Silverman learning styles visual* and *verbal*, the media preferences *text* and *image* are correlated with the data element *learning resource type*. Besides, the formats *video* and *audio* are related respectively to the media preference *video* and *audio*. When the learning resource type *simulation* is related to the media preference *simulation* with a degree 100%, the formats *application* and *example* can be associated to the media preference *simulation* too but with a degree less than 100% like 60%. In fact, *application, example, and simulation* have common pedagogical characteristics such as *their capabilities of explaining concepts, and abstracting reality*. Concerning the language preference, the data element *5.11language* is useful to check the appropriate language (The associations between values of the data element *5.11language* and some learners' characteristics have the same degree: 100%. In fact, the data element *5.11language* does not include a set of ranged values.). Regarding the personalization parameter *learner's level of knowledge*, the learners' characteristics included in it have a correlation with the values of the data element *difficulty*. For instance, a level of difficulty *easy* or *very easy* could be associated with the learners' characteristics *beginner* while a level of difficulty *difficult* or *very difficult* is associated with the characteristic *advanced* (The values *easy* and *very* easy are associated respectively with the degrees 80% and 100%. In fact *very* easy is the maximum degree of easiness. Similarly, the values *difficult* and *very difficult* are associated respectively with the degrees 80% and 100%.). Regarding the personalization parameters *motivation level*, its values *low*, *moderate* and *high* are associated respectively with the values *low (or very low)*, *medium* and *high* (*or very high*) of the data element *semantic density* (The semantic densities *low* and *very low* are associated respectively with the degrees 80% and 100%. In fact *very low* represents the lowest semantic density. The semantic densities *high* and *very high* are associated respectively with the degrees 80% and 100%. In fact *very high* represents the highest semantic density.). Last but not least, the values *objectivist* and *competency based* of the personalization parameter *pedagogical approach* are associated respectively with the values *educational objective* and *competency* of the data element purpose (The degree of this association is 100% because the values of the data element *purpose* are not ranged).

Table 1. Suggested relations between data elements and learners' characteristics

Data elements		**Learners' characteristics**		**Degree**
Metadata names prefixed by their reference numbers	***Metadata values***	***Linguistic terms***	***Personalization parameter***	
5.1 Interactivity Type 5.3 Interactivity Level	active very low	active	Felder-Silverman learning style	20%
5.1 Interactivity Type 5.3 Interactivity Level	active low	active	Felder-Silverman learning style	40%
5.1 Interactivity Type 5.3 Interactivity Level	active medium	active	Felder-Silverman learning style	60%
5.1 Interactivity Type 5.3 Interactivity Level	active high	active	Felder-Silverman learning style	80%
5.1 Interactivity Type 5.3 Interactivity Level	active very high	active	Felder-Silverman learning style	100%
5.1 Interactivity Type 5.3 Interactivity Level	expositive very low	reflective	Felder-Silverman learning style	20%
5.1 Interactivity Type 5.3 Interactivity Level	expositive low	reflective	Felder-Silverman learning style	40%
5.1 Interactivity Type 5.3 Interactivity Level	expositive medium	reflective	Felder-Silverman learning style	60%
5.1 Interactivity Type 5.3 Interactivity Level	expositive high	reflective	Felder-Silverman learning style	80%
5.1 Interactivity Type 5.3 Interactivity Level	expositive very high	reflective	Felder-Silverman learning style	100%
5.1 Interactivity Type 5.3 Interactivity Level	active very low	activist	Honey-Mumford learning style	20%
5.1 Interactivity Type 5.3 Interactivity Level	active low	activist	Honey-Mumford learning style	40%
5.1 Interactivity Type 5.3 Interactivity Level	active medium	activist	Honey-Mumford learning style	60%
5.1 Interactivity Type 5.3 Interactivity Level	active high	activist	Honey-Mumford learning style	80%
5.1 Interactivity Type 5.3 Interactivity Level	active very high	activist	Honey-Mumford learning style	100%
5.1 Interactivity Type 5.3 Interactivity Level	expositive very low	reflector	Honey-Mumford learning style	20%
5.1 Interactivity Type 5.3 Interactivity Level	expositive low	reflector	Honey-Mumford learning style	40%
5.1 Interactivity Type 5.3 Interactivity Level	expositive medium	reflector	Honey-Mumford learning style	60%
5.1 Interactivity Type 5.3 Interactivity Level	expositive high	reflector	Honey-Mumford learning style	80%
5.1 Interactivity Type 5.3 Interactivity Level	expositive very high	reflector	Honey-Mumford learning style	100%
5.2 Learning Resource Type	diagram	visual	Felder-Silverman learning style	100%
5.2 Learning Resource Type	figure	visual	Felder-Silverman learning style	100%
5.2 Learning Resource Type	graph	visual	Felder-Silverman learning style	100%
5.2 Learning Resource Type	narrative text	verbal	Felder-Silverman learning style	100%
5.2 Learning Resource Type	lecture	verbal	Felder-Silverman learning style	100%
4.1 Format	video	visual	Felder-Silverman learning style	100%
1.7 Structure	linear	sequential	Felder-Silverman learning style	100%
5.2 Learning Resource Type	simulation	simulation	Media preference	100%
5.2 Learning Resource Type	diagram	text/image	Media preference	100%
5.2 Learning Resource Type	figure	text/image	Media preference	100%
5.2 Learning Resource Type	graph	text/image	Media preference	100%
5.2 Learning Resource Type	narrative text	text/image	Media preference	100%
5.2 Learning Resource Type	lecture	text/image	Media preference	100%
4.1 Format	video	video	Media preference	100%
4.1 Format	audio	sound	Media preference	100%
4.1 Format	image	text/image	Media preference	100%
4.1 Format	text	text/image	Media preference	100%
4.1 Format	application	simulation	Media preference	60%
4.1 Format	example	simulation	Media preference	60%
1.3 Language	en	English	Language preference	100%

1.3 Language	de	German	Language preference	100%
1.7 Structure	hierarchical	global	Felder-Silverman learning style	100%
5.8 Difficulty	very easy	beginner	Learner's level of knowledge	100%
5.8 Difficulty	easy	beginner	Learner's level of knowledge	80%
5.8 Difficulty	medium	intermediate	Learner's level of knowledge	100%
5.8 Difficulty	difficult	advanced	Learner's level of knowledge	80%
5.8 Difficulty	very difficult	advanced	Learner's level of knowledge	100%
1.7 Structure	hierarchical	breadth-first	Navigation preference	100%
1.7 Structure	hierarchical	depth-first	Navigation preference	100%
5.4 Semantic Density	very low	low	Motivation level	100%
5.4 Semantic Density	low	low	Motivation level	80%
5.4 Semantic Density	medium	moderate	Motivation level	100%
5.4 Semantic Density	high	high	Motivation level	80%
5.4 Semantic Density	very high	high	Motivation level	100%
9.1Purpose	educational objective	objectivist	Pedagogical approach	100%
9.1Purpose	competency	competencies based	Pedagogical approach	100%

While there are several semantic relations between data elements and learners' characteristic presented in Table 1, additional similar relations can be defined and added by experts and other researchers in the E-learning domain. Besides, the data element *9 classification* could be used for representing other meaning coincidence with learners' characteristics. (This category of LOM standard describes where a learning object falls within a particular classification system. To define multiple classifications, there may be multiple instances of this category.) For example, the Blooms taxonomy for learning goal could be referenced with this data element and the learning goal level such as knowledge, comprehension and application could be cited with the data element 9.2.2 taxon (A particular term within a taxonomy. A taxon is a node that has a defined label or term.). In this way, the personalization parameter *learning goal* will be associated with the data element *classification of Blooms taxonomy*. In fact, the values of this personalization parameter have the same meaning of the referenced taxonomy values. In addition, the data element classification could be used several time for describing the same object (maximum: 40). So the defined relations could be easily extended based on this data element.

As demonstrated above, many works in literature have shown the usefulness of ontologies to store knowledge and reasoning about it. This work beneficiates from these capabilities of ontologies by storing the meaning coincidences between data elements and learners' characteristics in the form of an ontology, and by reasoning about these meaning coincidences. In particular, this paper shows the feasibility of reasoning about the stored meaning coincidences and generating suggestions for the usage of personalization strategies based on metadata of learning objects composing a course. Before presenting this reasoning capability, we introduce the adopted structure to store the relations between data elements and learners' characteristics in OSPS. Fig. 1 represents an overview of OSPS [1], which includes the relation between a data element and a learner characteristic (relation 4). In addition, it includes the description of the data element by its number, name and value (respectively by the relations 1, 2 and 3). OSPS supports the description of learners' characteristic as linguistic term (relation 5). It supports also the description of the personalization parameter which includes the learners' characteristics (relation 6). OSPS includes also the relation 7, which represents the degree of coincidence of a data element and a learners' characteristic.

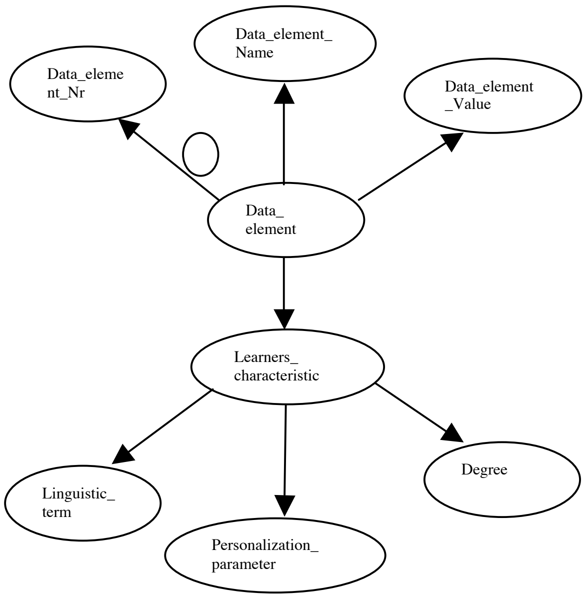

Fig. 1. Graphical representation of OSPS

4 Presentation of the Approach by an Example

This section presents an example explaining the proposed approach. The example is based on an extract of the course Compilation Theory (Table 2), and 9 semantic relations extracted from OSPS (Table 3). The extract of the course contains 3 concepts: *compilation*, *lexical analyzer*, and *syntactic analyzer*. The concept *compilation* is represented by 1 learning object: *communication between lexical and syntactic analyzer*. The concept *lexical analyzer* is represented by 2 learning objects: *overview of the lexical analyzer* and *detailed view of the lexical analyzer*. The concept *syntactic analyzer* is represented by 2 learning objects: *overview of the syntactic analyzer* and *detailed view of the syntactic analyzer*. All learning objects are annotated by some metadata. For example, the learning object *communication between lexical and syntactic analyzer* is annotated by the data element *5.8 Difficulty* having the value *easy*, the data element *5.1 Interactivity Type* having the value *active*, and the data element *5.3 Interactivity Level* having the value *very low*.

Table 3 presents 9 semantic relations between data elements and learners' characteristics (extracted from the 76 relation presented in Table 1). In addition, the table presents the degree of certainty about each relation. As an example of semantic relation, the data element *(5.8 Difficulty, very easy)* is related to the learners' characteristics *beginner*. The degree of certainty considered for this relation is 100%. As another example, the data elements *(5.1 Interactivity Type, active)* and *(5.3*

Interactivity Level, very low) together are related to the learners' characteristic *active* included in the personalization parameter *active/reflective dimension of Felder-Silverman learning style model*. The degree of certainty considered for this relation is 20%.

Table 2. Structure of the course Compilation Theory

Concepts	Learning objects	Metadata
Compilation	Communication between lexical and syntactic analyzer	(5.8 Difficulty, very easy), (5.1 Interactivity Type, active), (5.3 Interactivity Level, very low)
Lexical analyzer	Overview of the lexical analyzer	(1.7 Structure, hierarchical), (5.8 Difficulty, easy)
	Detailed view of the lexical analyzer	(1.7 Structure, linear), (5.8 Difficulty, difficult)
Syntactic analyzer	Overview of the syntactic analyzer	(1.7 Structure, hierarchical), (5.8 Difficulty, easy)
	Detailed view of the syntactic analyzer	(1.7 Structure, linear), (5.8 Difficulty, difficult)

Table 3. Matrix of semantic relation between data elements (extracted from LOM standard) and learners' characteristics

Data Element		**Learners' characteristics**		**Degree**
Metadata names prefixed by their reference number	***Metadata Values***	***Linguistic terms***	***Personalization parameters***	
5.8 Difficulty	very easy	beginner	Learner's level of knowledge	100%
5.8 Difficulty	easy	beginner	Learner's level of knowledge	80%
5.8 Difficulty	medium	intermediate	Learner's level of knowledge	100%
5.8 Difficulty	difficult	advanced	Learner's level of knowledge	80%
5.8 Difficulty	very difficult	advanced	Learner's level of knowledge	100%
5.1Interactivity Type	active	active	Active/reflective dimension of Felder-Silverman learning style model	20%
5.3Interactivity Level	very low			
5.1Interactivity Type	active	active	Active/reflective dimension of Felder-Silverman learning style model	100%
5.3Interactivity Level	very high			
1.7 Structure	linear	sequential	Sequential/global dimension of Felder-Silverman learning style model	100%
1.7 Structure	hierarchical	global	Sequential/global dimension of Felder-Silverman learning style model	100%

Table 4 presents a matrix of appropriate learning objects generated from the structure of the course presented in Table 2 and the semantic relations presented in Table 3. In this matrix, concepts are presented in rows, and personalization parameters are presented in columns. In addition, each column is divided in sub-columns presenting the learners' characteristics included in the personalization parameter presented in the column. Each cell of the matrix contains the learning objects representing a specific concept and appropriate to a specific learners' characteristic. Besides a learning object, the degree of its appropriateness to the learners' characteristic is represented. Concerning the automatic filling of the cells with appropriate learning objects, a subset of data elements describing learning objects is used as input for the semantic relations between data elements and learners' characteristics. For example, the description of the learning object *communication between lexical and syntactic analyzer* (in Table 2) with the data element *(5.8 Difficulty, very easy)* is an input for the semantic relation (in Table 3) between the same data element and the learners' characteristic *beginner* included in the personalization parameter *learner's level of knowledge*. As a consequence, the learning object *communication between lexical and syntactic analyzer* is placed in the cell intersection of the row representing the concept *compilation* and the sub-column representing the learners' characteristic *beginner*. As another example, the description of the learning object *communication between lexical and syntactic analyzer* with the two couples *(5.1 Interactivity Type, active)* and *(5.3 Interactivity Level, very low)* is an input for the relation between these two couple and the triple *(active, active/reflective dimension of Felder-Silverman learning style model, 20%)*. As a consequence, the learning object *communication between lexical and syntactic analyzer* is placed in the cell intersection of the row representing the concept *compilation* and the sub-column representing the learners' characteristic *active*. In addition, the degree of appropriateness of the learning object is *20%*. In the same way, the learning objects representing the concepts *lexical analyzer* and *syntactic analyzer* are used to fill the cells of the rows representing these concepts. This filling is based on the descriptions of the learning objects that are used as input for the semantic relations represented in Table 3. However, some cells are empty. A cell is empty if no learning object exists that represents the concept in row and is appropriate to the learners' characteristic in the sub-column. For example, the cell intersection of the row *compilation* and the sub-column *sequential* is empty due to the fact that there is no learning object representing the concept *compilation* and appropriate to the learners' characteristic *sequential*. In fact, Table 2 does not contain a learning object representing the concept *compilation* and described with the data element *(1.7 Structure, linear)* which is the only input (in Table 3) to get the learners' characteristic *sequential*.

Table 4. Matrix for Appropriate Learning Objects

	Learner's level of knowledge			**Active/reflective dimension of Felder-Silverman learning style model**		**Sequential/global dimension of Felder-Silverman learning style model**	
	beginner	***intermediate***	***advanced***	***active***	***reflective***	***sequential***	***global***
Compilation	Communication between lexical and syntactic analyzer (100%)			Communication between lexical and syntactic analyzer (20%)			
Lexical analyzer	Overview of the lexical analyzer (80%)		Detailed view of the lexical analyzer (80%)			Detailed view of the lexical analyzer (100%)	Overview of the lexical analyzer (100%)
Syntactic analyzer	Overview of the syntactic analyzer (80%)		Detailed view of the syntactic analyzer (80%)			Detailed view of the syntactic analyzer (100%)	Overview of the syntactic analyzer (100%)

Table 5 presents 2 metrics for comparing personalization parameters as well as results of these metrics for particular personalization parameters. The first metric is CRCH (Concept Represented for learners' Characteristics) which is based on the number of cells filled by appropriate learning objects divided by the number of cells in the column. This metric does not consider the degrees of learning objects appropriateness. It considers only two values: 1 for non empty cells (contains appropriate learning objects) and 0 for empty cells (when no appropriate learning object exists). As an example, for the personalization parameter *learners' level of knowledge* (in Table 4), 5 cells contain appropriate learning objects where the total number of cells for the same personalization parameter is 9. In this case, the value of CRCH is 5/9 = 0.55. As another example, the CRCH for the personalization parameter *Active/reflective dimension of Felder-Silverman* learning style model is 1/6 = 0.16 which does not constitute a good rate. This is explained by the fact that with the current set of learning objects, *active* learners beneficiate from personalization only from the concept *compilation* and *reflective* learners do not beneficiate from personalization of the course (according to the Table 4, no learning object exists which would be appropriate for them). Concerning the metric CRCHDegree (Concept Representation for a learners' CHaracteristic with a Degree), the degree of appropriateness of learning objects to the learners' characteristics is considered. For example, the value of CRCHDegree for the personalization parameters *learners' level of knowledge* is (1+0.8+0.8+0.8+0.8)/9=0.46. This metric, like CRCH, depend on the number of cells containing appropriate learning objects. In addition, it depends on the degree of appropriateness to learners' characteristics. As a conclusion, both CRCH and CRCHDegree can be used for comparing personalization parameters with respect to the rate of learning objects representing different concepts and the appropriateness to divergent learners' characteristics. In fact, the values of CRCH and CRCHDegree are real numbers (□) which are ordered. The maximal value of CRCH is 1. This value is achieved when for each concept at least one learning object exists that is appropriate to each learners' characteristic included in a personalization parameter. In this case, all learners benefit from the personalization based on this personalization parameter. The maximal value of CRCHDegree is 1. This value is achieved when for each concept at least one learning object exists that is appropriate with a degree of 100% to each learners' characteristic included in a personalization parameter. The minimal value for CRCH and CRCHDegree is 0. This value is achieved when no learning object exists that is appropriate to any learners' characteristics included in a given personalization parameter. In this case, no learner would benefit from the personalization based on this personalization parameter.

Table 5. Comparing personalization parameters based on CRCH and CRCHDegree

	CRCH	**CRCHDegree**
Learner's level of knowledge	5/9 = 0.55	(1+0.8+0.8+0.8+0.8)/9=0.46
Active/reflective dimension of Felder-Silverman learning style model	1/6 = 0.16	0.2/6=0.03
Sequential/global dimension of Felder-Silverman learning style model	4/6= 0.66	(1+1+1+1)/6=0.66

Table 6 presents two additional metrics for comparing personalization parameters: CRP (Concept Represented for personalization Parameter) and CRPDegree (Concept Represented for personalization Parameter with a Degree). These two metrics are calculated respectively in the same way of calculating CRCH and CRCHDegree. The particularity of these two metrics is the consideration of concepts which are represented by learning objects complementarily appropriate to all learners characteristics included in a given personalization parameter. These metrics look into whether each concept can be taught for each learner considering their different characteristics based on the respective personalization parameter and therefore favors the selection of personalization parameters which allow different learners to beneficiate from the personalization. For example, there are 0 concepts complementarily represented by appropriate learning objects to the learners' characteristics included in the personalization parameter *learner's level of knowledge* (since there is no learning object available for intermediate learners). This low rate excludes the personalization parameter *learner's level of knowledge* which does not allow personalization of concepts for all learners. In fact, the column representing this personalization parameter in Table 4 contains at least an empty cell for each concept.

As another example, there are 2 from 3 (2/3 = 0.66) concepts complementarily represented by appropriate learning objects to the learners' characteristics included in the personalization parameter *sequential/global dimension of Felder-Silverman learning style model*. In this case the two concepts are represented by learning objects appropriate to the learners' characteristics with a degree *100%*. For that reason, the value of CRP is equal to the value of CRPDegree (for the degrees 0 and 1, we have the same results when considering CRP or CRPDegree).

Table 6. Comparing personalization parameters based on CRP and CRPDegree

	CRP	**CRPDegree**
Learner's level of knowledge	0	0
Active/reflective dimension of Felder-Silverman learning style model	0	0
Sequential/global dimension of Felder-Silverman learning style model	0.66	0.66

5 Experiment

The objective behind the specification of OSPS is to put in order personalization strategies for each course. The comparison of personalization strategies is based on the coincidence of data elements extracted from LOM standard with the learners' characteristics included in the personalization parameters. In order to test the proposed approach, 260 learning objects representing 40 concepts included in 3 courses and the 76 instances of semantic relations presented in Table 1 are used for comparing 12 personalization strategies (4 ways of selecting personalization parameters are applied on 3 courses). The 3 courses are about Microsoft Excel (includes 53 learning objects representing 8 concepts), Programming Language C (includes 67 learning objects representing 5 concepts), and Databases (includes 140 learning objects representing 27 concepts). The 260 learning objects are annotated with metadata by using the tool Reload Editor[3] and an IMS package[4] is generated for each course with the same tool. Then, each IMS package is used to put in order personalization strategies of the associated course based on the approach presented in the previous section.

In order to test OSPS and the proposed approach, the most significant personalization parameters selected manually by students in a past experiment (without using OSPS and metadata describing learning objects) are compared with the most significant personalization parameters generated based on OSPS and the metadata describing learning objects. A past study (January–February 2009) focused on the specification of personalization strategies [2]. The detailed procedure about this first study and the reliability rates are presented in [2]. The participants were third year students (computer science). They were asked to individually update manually the cells of the matrix containing appropriate learning objects for three delivered courses (Programming Language C, Databases, and Microsoft Excel). Columns and

[3] http://www.reload.ac.uk/editor.html
[4] http://www.imsglobal.org/content/packaging/

rows of the matrix were given to the students. They were asked also to determine manually the most significant personalization parameters for each course according to the number of learning objects and their average appropriateness to the characteristics included in the personalization parameters. Each student was asked to select the two most significant personalization parameters for each course. Table 7 shows the total number of times that each personalization parameter appeared as one of the two most significant one for each course. As an example, for the course Programming Language C, the personalization parameter *active/reflective dimension of the Felder–Silverman learning style model* was selected by the highest number of students (17 times). Table 8 shows the values of the metrics CRCH, CRCHDegree, CRP, and CRPDegree for each personalization parameter personalizing each course, calculated based on OSPS and the approach explained in Section 4. The previous experiment and the current experiment have the same objective which is the selection of the most significant personalization parameters for each course. The most significant parameters in the previous experiment were selected by student. The most significant parameters in the current experiment are automatically identified based on CRCH, CRCHDegree, CRP, and CRPDegree. Since the personalization parameters included in our current study changed slightly from the personalization parameters included in the previous study, only personalization parameters are included in the comparison that are included in both tables. In particular, the personalization parameters *navigation preference* and *motivation level* are eliminated from Table 8. These personalization parameters were not proposed by the teacher in the previous experiment in the structure of the matrix used for the selection of appropriate personalization parameters. In addition, the personalization parameter s*ensing/intuiting dimension of the Felder–Silverman learning style model* is eliminated from Table 7. The learners' characteristics of this personalization parameter are not included in OSPS. Currently, we do not observe any semantic relations between data elements of LOM standard and the learners' characteristics s*ensing* and *intuiting*.

Table 7. Number of times that personalization parameters appeared as one of the most significant one Through Manual Selection

Personalization parameter	Courses			Total
	Programming Language C	Data base	Microsoft Excel	
Active/reflective dimension of the Felder–Silverman learning style model	17	10	3	30
Visual/verbal dimension of the Felder–Silverman learning style model	2		7	9
Sequential/global dimension of the Felder–Silverman learning style model			3	3
Honey–Mumford learning style		3	2	5
Learner's level of knowledge	13	15	5	33
Media preference	8	2	11	21

Table 8. Results for the metrics used in current experiment

Part 1. Results for the metrics CRCH and CRCHDegree

Personalization parameter	Courses						Total of CRCH	Total of CRCH Degree
	Programming Language C		Data base		Microsoft Excel			
	CRCH	CRCHDegree	CRCH	CRCHDegree	CRCH	CRCHDegree		
Active/reflective dimension of the Felder–Silverman learning style model	1	0.76	0.70	0.49	0.87	0.55	2.57	1.8
Visual/verbal dimension of the Felder–Silverman learning style model	0.6	0.60	0.74	0.74	0.56	0.56	1.9	1.9
Sequential/global dimension of the Felder–Silverman learning style model	0	0.00	0.01	0.01	0.00	0.00	0.01	0.01
Honey–Mumford learning style	0.5	0.38	0.35	0.24	0.43	0.27	1.28	0.89
Learner's level of knowledge	0.8	0.70	0.62	0.55	0.37	0.35	1.79	1.6
Media preference	1	0.80	0.64	0.58	0.87	0.87	2.51	2.25

Part 2. Results for the metrics CRP and CRPDegree

Personalization parameter	Courses						Total of CRP	Total of CRP Degree
	Programming Language C		Data base		Microsoft Excel			
	CRP	CRPDegree	CRP	CRPDegree	CRP	CRPDegree		
Active/reflective dimension of the Felder–Silverman learning style model	1	0.76	0.4	0.26	0.75	0.45	2.15	1.47
Visual/verbal dimension of the Felder–Silverman learning style model	0.2	0.2	0.48	0.48	0.12	0.12	0.8	0.8
Sequential/global dimension of the Felder–Silverman learning style model	0	0	0	0	0	0	0	0
Honey–Mumford learning style	0	0	0	0	0	0	0	0
Learner's level of knowledge	0.4	0.34	0.18	0.15	0	0	0.58	0.49
Media preference	1	0.80	0.29	0.23	0.75	0.75	2.04	1.78

Table 9 presents the distances[5] between the ranks of appropriate personalization parameters in the past study and their ranks in the current experimentation. In particular, it presents the DPCRCH (Distance between the rank of a personalization parameter in the Past study and its rank according to CRCH), DPCRCHDegree (Distance between the rank of a personalization parameter in the Past study and its rank according to CRCHDegree), DPCRP (Distance between the rank of a personalization parameter in the Past study and its rank according to CRP), and DPCRPDegree (Distance between the rank of a personalization parameter in the Past study and its rank according to CRPDegree). Each of these distances is calculated for each course (in sub-column), for each personalization parameter (in row). Most of these distances are low compared to the maximal distance which is 5 (the maximal distance is the distance between the maximal rank and the minimal rank = 6-1 =5). As an example, for the course *Programming Language C* and the personalization parameter *active/reflective dimension of the Felder–Silverman learning style model*, these distance are: DPCRCH =0 (=1-1. The rank of the personalization parameter *active/reflective dimension of the Felder–Silverman learning style model* for the course *Programming Language C* in the past experimentation is equal to its rank according to the metric CRCH =1. In fact, in the past experimentation, this

[5] The distance between two ranks = the higher rank –the lower rank. For example, the distance between the rank 1 and the rank 3=3-1=2.

personalization parameter is selected by the highest number of students. Besides, this personalization parameter have the highest rate according to CRCH in the current experimentation.), DPCRP = 0 (=1-1), DPCRCHDegree = 1 (=2-1), and DPCRPDegree =1 (=2-1).

Table 9. Distances between the ranks of appropriate personalization parameters in the past study and their ranks in the current experimentation.

Part 1. DPCRCH and CRCHDegree

Personalization parameter	Courses						Average of DP CRCH	Average ofDP CRCH Degree	Mediane of DP CRCH	Mediane of DP CRCH Degree
	Programming Language C		Data base		Microsoft Excel					
	DPCRCH	DPCRCH Degree	DPCRCH	DPCRCH Degree	DPCRCH	DPCRCHDegree				
Active/reflective dimension of the Felder–Silverman learning style model	0	1	0	2	3	1	1	1.33	0	1
Visual/verbal dimension of the Felder–Silverman learning style model	0	0	4	4	1	0	1.6	1.33	1	0
Sequential/global dimension of the Felder–Silverman learning style model	1	1	1	1	2	2	1.3	1.33	1	1
Honey–Mumford learning style	0	0	2	2	2	1	1.33	1	2	1
Learner’s level of knowledge	1	1	3	2	2	1	2	1.33	2	1
Media preference	2	2	1	2	0	0	1	1.33	1	2
Average	0.66	0.83	1.83	2.16	1.66	0.83	1.38	1.27	1.16	1
Mediane	0.5	1	1.5	2	2	1	1.33	1.33	1	1

Part 2. DPCRP and CRPDegree

Personalization parameter	Courses						Average of DP CRP	Average ofDP CRP Degree	Mediane of DP CRP	Mediane of DP CRP Degree
	Programming Language C		Data base		Microsoft Excel					
	DPCRP	DPCRP Degree	DPCRP	DPCRP Degree	DPCRP	DPCRP Degree				
Active/reflective dimension of the Felder–Silverman learning style model	0	1	0	0	3	2	1	1	0	1
Visual/verbal dimension of the Felder–Silverman learning style model	0	0	4	4	1	1	1.66	1.66	1	1
Sequential/global dimension of the Felder–Silverman learning style model	0	0	0	0	0	0	0	0	0	0
Honey–Mumford learning style	0	0	2	2	2	2	1.33	1.33	2	2
Learner’s level of knowledge	1	1	3	3	1	1	1.66	1.66	1	1
Media preference	2	2	1	1	0	0	1	1	1	1
Average	0.5	0.66	1.66	1.66	1.16	1	1.11	1.11	0.83	1
Mediane	0	0.5	1.5	1.5	1	1	1.16	1.16	1	1

DPCRCH: Distance between the rank of a personalization parameter in the Past study and its rank according to CRCH;

DPCRCHDegree: Distance between the rank of a personalization parameter in the Past study and its rank according to CRCHDegree;

DPCRP: Distance between the rank of a personalization parameter in the Past study and its rank according to CRP;

DPCRPDegree: Distance between the rank of a personalization parameter in Past study and its rank according to CRPDegree;

These low distances show good similarity between the ranks of appropriate personalization parameters in the past study and their ranks in the current experimentation. In particular, 24 values of these distances are 0 (according to Table 9) which is the lowest distance. Averages and medians of these distances are calculated for each personalization parameter (in the last 4 column of Table 9) and for each course (in the last two rows of Table 9). Again, these average and medians show good similarity between the ranks of appropriate personalization parameters in the past study and their ranks in the current experimentation. As an example, for the personalization parameter *active/reflective dimension of the Felder–Silverman learning style model*, the average of DPCRCH and DPCRP is 1 which shows a good similarity compared to the maximal distance (=5). In addition, for the same personalization parameter, median of DPCRCH, and median of DPCRP is 0. This median shows that 50% of the ranks for this personalization parameter are equal in both experimentations (the past and the current experimentation).

6 Conclusion and Perspectives

In this paper, we presented and evaluated an approach for the automatic comparison of personalization strategies as well as their application for generating personalized learning scenarios. The proposed approach is based on OSPS which is an ontology describing semantic relations between data elements of LOM standard and learners characteristics included in personalization parameters. OSPS can be used for defining order relations based on Boolean logic and Fuzzy logic. Each of these logics has been tested with OSPS on 260 learning objects representing 40 concepts included in 3 courses. As a result, it is shown that the proposed approach could be used to enhance the productivity in adaptive learning by automatically determining the appropriate learning objects to learners' characteristics, and the prevision of appropriate personalization strategies.

Concerning the appropriate learning objects to learners' characteristics, the proposed approach exploit learning object annotated with LOM standard and semantic relations between data elements and learners' characteristics to determine learning objects appropriate to learners' characteristics.

Concerning the prevision of appropriate personalization strategies, the proposed approach defines 4 metrics (2 based on Boolean logic, which are CRCH and CRP, and 2 are based on fuzzy logic, which are CRCHDegree and CRPDegree) for effectiveness of personalization strategies.

Future directions of this research will deal with extending OSPS for describing the Web services implementing the personalization parameters (including the URL of the Web service, available functions, organizations, researchers working on the personalization parameters, etc.). This extension will facilitate the reuse of the personalization parameters. Furthermore, OSPS will be extended by considering additional data elements, learners' characteristics and semantic relations between them.

Acknowledgments. Authors acknowledge Ms. Awatef Essalmi Ben Arbia for the annotation of learning objects with metadata, and the students of the ESST Tunis who participated in the implementation of the tool which automates the presented approach. Authors acknowledge also the Ministry of Higher Education, Scientific Research and Technology of Tunisia for its Grant to the Research Laboratory UTIC.

This research is supported in part by the NSERC, iCORE, Xerox, and the research related funding by Mr. A. Markin.

References

1. Essalmi, F., L. J. B. Ayed, M. Jemni.: An ontology based approach for selection of appropriate E-learning personalization strategy. ICALT, 724--725 (2010).
2. Essalmi, F., L. J. B. Ayed, M. Jemni, Kinshuk, S. Graf.: A fully personalization strategy of E-learning scenarios. Computers in Human Behavior 26, Elsevier, 581--591 (2010).
3. IEEE, Inc. Draft Standard for Learning Object Metadata. (2002).
4. Wang, H-C., Hsu, C-W.: Teaching-Material Design Center: An ontology-based system for customizing reusable e-materials. Computers & Education 46, 458--470 (2006).
5. Zeng, Q., Zhao, Z., Liang, Y.: Course ontology-based user's knowledge requirement acquisition from behaviors within e-learning systems. Computers & Education 53, 809--818 (2009).
6. Sancho, P., Martínez, I., Fernández-Manjón, B.: Semantic Web Technologies Applied to e-learning Personalization in <e-aula>. Journal of Universal Computer Science, vol. 11, no. 9, 1470--1481 (2005).
7. Henze, N., Dolog, P., Nejdl W.: Reasoning and Ontologies for Personalized E-Learning in the Semantic Web. Educational Technology & Society, 7 (4), 82--97 (2004).
8. Kontopoulos, E., Vrakas, D., Kokkoras, F., Bassiliades, N., Vlahavas, I.: An ontology-based planning system for e-course generation. Expert Systems with Applications 35, 398--406 (2008).
9. Chi, Y-L.: Ontology-based curriculum content sequencing system with semantic rules. Expert Systems with Applications 36, 7838--7847 (2009).
10. Isotani, S., Inaba, A., Ikeda, M., Mizoguchi, R.: An Ontology Engineering Approach to the Realization of Theory-Driven Group Formation. International Journal of Computer Supported Collaborative Learning, 4(4), Springer. 2009. Available at: http://dx.doi.org/10.1007/s11412-009-9072-x.
11. Jiang, X., Tan, A-H.: Learning and inferencing in user ontology for personalized Semantic Web search. Information Sciences 179, 2794--2808 (2009).
12. Weng S-S., Chang, H-L.: Using ontology network analysis for research document recommendation. Expert Systems with Applications 34, 1857--1869 (2008).
13. Gladun, A., Rogushina, J., García-Sanchez, F., Martínez-Béjar, R., Fernández-Breis, J. T.: An application of intelligent techniques and semantic web technologies in e-learning environments. Expert Systems with Applications 36, 1922--1931 (2009).
14. Žitko, B., Stankov, S., Rosić, M., Grubišić, A.: Dynamic test generation over ontology-based knowledge representation in authoring shell. Expert Systems with Applications 36, 8185--8196 (2009).
15. Eriksson, H.: The semantic-document approach to combining documents and ontologies. Int. J. Human-Computer Studies 65, 624--639 (2007).
16. Lu, E. J-L., Hsieh, C-J. : A relation metadata extension for SCORM Content Aggregation Model. Computer Standards & Interfaces 31, 1028--1035 (2009).
17. Hsu, I-C., Chi, L-P., Bor, S-S.: A platform for transcoding heterogeneous markup documents using ontology-based metadata. Journal of Network and Computer Applications 32, 616--629 (2009).
18. Felder, R. M., & Silverman, L. K..: Learning and teaching styles in engineering education. Engineering Education, 78(7), 674--681 (1988).
19. Felder, R.M., Soloman, B.A.: Learning styles and strategies. Available from http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSdir/styles.htm (2010).

20. Honey, P., & Mumford, A.: A manual of learning styles. In Peter Honey & Maidenhead (Eds.), Learning styles. Engineering Subject Centre (1986).
21. Kolb, D. A.: Experiential learning: Experience as the source of learning and development. NJ: Prentice-Hall. In David A. Kolb, Richard E. Boyatzis, Charalampos Mainemelis (Eds.), Experiential learning theory: Previous research and new directions (1984).
22. Keller, J. M.: Motivational design of instruction. In C. M. Reigeluth (Ed.), Instructional design theories and models: An overview of their current status. Hillsdale, NJ: Erlbaum (1983).
23. Small, R. V.: Motivation in instructional design. NY: ERIC Clearinghouse on Information and Technology Syracuse (1997). Available from http:// www.ericdigests.org/1998-1/motivation.htm.
24. Essalmi, F., Jemni Ben Ayed, L., Jemni, M.: A multi-parameters personalization approach of learning scenarios. In The 7th IEEE international conference on advanced learning technologies, Niigata, Japan, 90--91 (2007).