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How e-learning systems may benefit from ontologies and recommendation methods to efficiently personalise resources

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Abstract: Knowledge management systems suffer from the efficient management of the information they maintain. Current e-learning systems, is an application of a progressively more complex information domain, as they increasingly enhance their courses with the variety of web based resources to meet the educational needs of their participants. Thus, they face the problem of managing and personalising this knowledge. To confront this problem they already benefited from the semantic web technologies. Ontologies, a cardinal asset towards augmenting the interoperability among web applications, anticipate the accuracy of the retrieved data by means of effective matching of the user requirements. In this paper ontologies are explored to personalising resources. The framework of an e-learning system is described and a methodology is proposed applying recommendation algorithms. Personalisation is achieved via handling related metadata of the attendants' personality and preferences, as well as, reputation metadata, thus anticipating their satisfaction and educational progress.

Keywords: knowledge management; e-learning; semantic web; ontology; recommendation; personalisation; learning style

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1   Introduction

The considerable amount of knowledge through various documents within organisations increasingly grows. Their efficient maintenance and meaningful retrieval is of great importance. Synchronous e-learning systems is a kind of informational systems as they handle a great amount of resources and enhance their courses from the plethora of the electronically accessible resources located in various websites. In such systems, the availability of a huge amount of information for the same educational purpose allows the learner to choose the most suitable among them. This is crucial in e-learning systems because, according to Jonassen et al. (1993) "…individuals differ in their general skills, aptitudes, learning styles and preferences for processing information, the way they construct meaning from it and applying it to new situations". Although the availability of a variety of resources is an important feature of the e-learning systems towards to meet the different needs of their audiences, on the other hand, this variety raises the issue of the efficient knowledge retrieval. Thus, much effort has been done to enhance current e-learning systems with mechanisms that facilitate the personalised resource selection to the needs of the individual.

2   Background and related work

Current e-learning systems benefit from the emerging technologies of the semantic web in order to facilitate the appropriate resource selection. Berners Lee et al. (2002) proposed the semantic web as an infrastructure developed upon the current web, to

confront the major problem of information retrieval that is to find out more accurate and meaningful resources. A main advantage of this infrastructure is that it is based on a well-established mechanism that makes the information machine-interpretable and allows syntactic and semantic interoperability among web applications. Using this infrastructure the properties of a resource are described through metadata and not on its actual content. A main tool of the semantic web technologies is ontologies. An ontology is a catalogue of the types of things that exist in a domain of interest D from the perspective of a person who uses a language L to talk about D (Sowa, 2000). Ontologies essentially define a classification, implementing a class-subclass hierarchy between the concepts, the vocabulary and types of arguments that can be used in the domain and a set of rules that derive new information from the existent. Several languages were defined to describe ontologies, e.g., F-logic. F-logic represents the concept as a knowledge structure, along with the relationships connecting it to other concepts. An F-logic rule consists of a 'head' and a 'body'. Syntactically, it starts with the word FORALL, the head of the rule follows, separated by the body with the symbol ←. The body is an arbitrary long logical expressions combined with AND (∧), OR (∨), NOT (¬) operators. Variables, represented using the symbol @, may be part of the rules. F-logic also creates queries which are rules without a head. An example of an F-logic rule is:

```
FORALL X:Learner,X[hasCertification → HigherEducation] ←
X[hasCertification → Msc].
```

which means that if X is a learner and he has a 'master' degree then he must also have a certification from a 'higher educational' institute. A tutorial about F-logic can be found on 'How to write F-logic programs'.

To further facilitate the development of e-learning systems and support interoperability between them, educational standards were also designed to describe their concepts, namely the learner and the learning resource. The standards lead to the systems' further development. The most popular of the standards used to describe the learning resource is learning standard metadata – LOM – (the specifications of which are located on Learning Technology Standards Committee of the IEEE) due to its ability to describe a large range of the attributes of a resource which is suitable for educational purposes. LOM uses a pre-defined vocabulary to describe the content of the learning resources. The terms of this vocabulary are classified in nine main categories:

1   general that groups the general information that describes the resource as a whole

2   life-cycle, that describes the features related to the history and current state of this resource, and those who have affected this resource during its evolution

3   meta-metadata, that describes information about the meta-data itself

4   technical, that describes the technical requirements and characteristics of the resource

5   educational, groups the educational and pedagogic characteristics of the resource

6   rights that defines the rights and conditions of use for the resource

7   classification, describe the classification of a recourse

8   annotation, that provides comments on the educational use of the resource and
      information on when and by whom the comments were created.

There are tools that facilitate the proper description of the learning resources in RDF
format under the LOM standard, e.g., SHAME – Standardised Hyper Adaptable Metadata
Editor (2008).

Similarly, many standards (e.g., LIP, PAPI, Dolog LP) have been proposed to
describe the learner's personality. PAPI (IEEE P1484.2.1/D8) defines the personal
information, and qualifications, skills, licenses etc the learner has acquired during his
life. E.g., the 'certifications' entry of PAPI describes the learner experience in a
knowledge domain; the 'preferences' describes his language or document-type
preferences etc.

A third dimension that was extremely examined for its affection on the learning
process is the individual's learning style. Keefe (1991), states that learning style is
both a student characteristic and an instructional strategy. As a student characteristic,
learning style indicates how a student learns and likes to learn. As an instructional
strategy, it informs about the cognition, context, and content of learning. Researches of
Roy and Chi (2003) and Park and Black (2007) examined whether the conjunction of
the learner's characteristics that derive from his learning style and the characteristics of
the learning resource affect the learner's performance or the way he approaches the
learning process. Merrill (2000) concluded that the learning style is not the only
primary factor in selecting the fundamental components of an instructional
strategy appropriate for and consistent with a given learning goal. However it should
be considered in selecting instructional style and adjusting the parameters in
order to create an instructional strategy. Several questionnaires (indicatively
VARK, 2006) are electronically available and let an individual to find out his learning
style.

The goals of the semantic web technologies and the educational standards enhance
personalised retrieval. Earlier efforts assessed personalisation using pre-defined rules that
sequentially proposed learning resources in a specified sequence subject to the learner's
educational progress. Henze et al. (2004) use of the semantic web technologies on
personalisation and described an e-learning system in which they designed a set of rules.
These rules proposed learning resources in a predefined learning path. In order to offer
personalised material Ochoa and Duval (2006) exploited recommendation methods in
e-learning systems, mainly used in e-commerce systems and collaborative networks.
Towards the same direction, Wang et al. (2007) proposed a system based on
recommendation methods. As mentioned from Resnick and Varian (1997) the
functionality of the recommendation systems differs from the one of the search systems.
Search systems retrieve items according to their actual properties/content.
Recommendation systems collect explicit and implicit feedback provided for the
resources by users in the past to predict resources for the current users. Explicit feedback
is gathered when a user rates an item as interesting or relevant. It is of great importance,
as it comes from users that are interested in the knowledge domain the resource belongs
to. On the other hand, implicit feedback is extracted from user actions and provides some
evidence about item quality or relevance, such as link selection, reading time,
bookmarking etc.

As summarised from Wang et al. (2007), the recommendation methods are divided in
three main categories: content-based, collaborative-based and hybrid. The content-based

methods are based on the idea that if a user asked for an item in the past he would probably ask for the same item in the future. The collaborative-based methods find items for the current user based on the choices of similar ones. Hybrid methods take advantage of both strategies and therefore they usually conclude to better results. All methods keep track of the items a user has consumed. These methods extract the features of the items and maintain them in the profile of the user. The profile is gradually built as the user searches for resources. In these systems the profile constitutes from the characteristics of the resources he has consumed. This is a major difference between them and e-learning systems as the latter must to be aware about the learners' actual characteristics that derive from his personality and pedagogic theories. The e-learning systems have a lot of available information about the characteristics of the learner, provided:

a   along with his registration in the system

b   acquired gradually during his attendance.

This information concerns the lessons he studied, his performance, his participation in several educational activities etc. Finally, in an e-learning system the attendant is supervised and guided to his educational progress – otherwise it tends to be a self-training system. After all, e-learning systems are not search-engines, although they have to include a search-mechanism to facilitate the learner's informational needs according to the above mentioned parameters.

2.1   Motivation scenario

In the following article all the above mentioned factors, i.e., semantic web technologies, educational standards and learning style outcomes, are correlated to describe a semantic-web based e-learning system. A semantic web-based framework is described. In this framework two ontologies are designed to describe the properties of the two concepts of a learning system. A third ontology is also designed to collect reputation metadata of the learners for the learning resources and to further correlate their instances (Kerkiri et al. 2007). In this framework a methodology is also proposed. This methodology attempts personalisation by aligning properties of the two ontologies, characteristics of the learner to characteristics of the learning resources. We exploit recommendation methods based on evaluations, as well as, learning style suggestions. Due to the broad application of semantic web technologies and educational standards, our effort can extend existing ontologies. It can also be adopted by various learning management systems (LMSs) that are oriented towards semantic web technologies. An advantage of our system is that it was implemented in a modular manner. As a result, the functionality of each of its modules is implemented independently. Hence any alternative algorithm can be used.

The remaining of this paper is organised as follows: Section 2 presents the proposed e-learning system and the ontologies. Section 3 describes the recommendation architecture and the similarity model, as well as the hybrid retrieval and recommendation algorithm. An evaluation of the system is presented in Section 4. Finally, the conclusions are discussed in the last section.

3   The e-learning system

3.1   The proposed framework

The learners of this system initially have to provide some information about them, using the PAPI standard, concerning their personal details, preferences etc. This information fills the learner's ontology. Moreover, the registered learners have to complete a learning style questionnaire.

The learning resource is described using the LOM standard. The filling of the LR ontology can initially be accomplished by automated extraction of metadata about resources distributed in the web. Efforts such as Java et al. (2006) propose methods to automatically extract annotations about web resources using natural language processing techniques. This approach is not always possible though, due to the fact that suitable metadata of several categories can not always be extracted from text descriptions, or, if found, it is not classified under a specific standard. The latter can be confronted by aligning several standards (such as LIP/PAPI, as mentioned from Dolog and Schafer, 2005). In any case though, the quality and the pedagogic results of the specific resource cannot be described from an automated process. Thus, according to our scenario, domain experts from collaborative nodes feed a central data repository with metadata about a variety of learning resources that are now available in the local repositories or in various web-sites. They extract information about LRs from plain text format and convert it to suitable LOM entries. This extra effort though anticipates the increase of personalisation.

Entries of LOM standard that are of immediate interest of this research are the educational and classification ones. There are several standards that provide a classification of the resources, e.g., Dewey or library of congress classification systems. The adoption of a standard classification system facilitates the classification of the resources and, at the same time, eliminates the problem of creating an unlimited amount of information about a specific topic that covers all situations, as the current information can be easily updated or integrated into a larger hierarchy. Someone may notice that many sites providing scientific resources already use a classification. The material being distributed concerns multimedia courses. The resources of this course are categorised under ACM classification (ACM Computing Classification System: Top 2 Levels, 1998), which is a specific classification system especially designed for the information theory. Under ACM, the entry H.5.1 is used to classify the 'multimedia' material. Further classification of this entry is animations, artificial realities, audio I/O, evaluation/methodology, hypertext navigation and maps, video. We have focused on the 'animations' entry. A great range of material about web design and image processing tools were created and properly annotated. The feed of the LR ontology is achieved by searching in online bookstores, and dedicated various websites. If the resource is not sufficiently described the consumers of this resource are allowed to provide adequate description metadata.

From each instance of our data repository links to a number of URLs depicting to different instances of the same resource are possible. These links start from the current repository and point to different instances of the LR. In this way its availability is increased.

The framework of the proposed system is shown in Figure 1.

After the completion of the annotation phase, the learners are encouraged to use this repository and select among the set of the available resources to cover their educational needs. Each node applies its own policy before revealing the LR to the learner. Each learning resource the learner uses is attached to his profile. After the use of a resource the learner is also encouraged to offer an evaluation for it.

Figure 1 The proposed framework
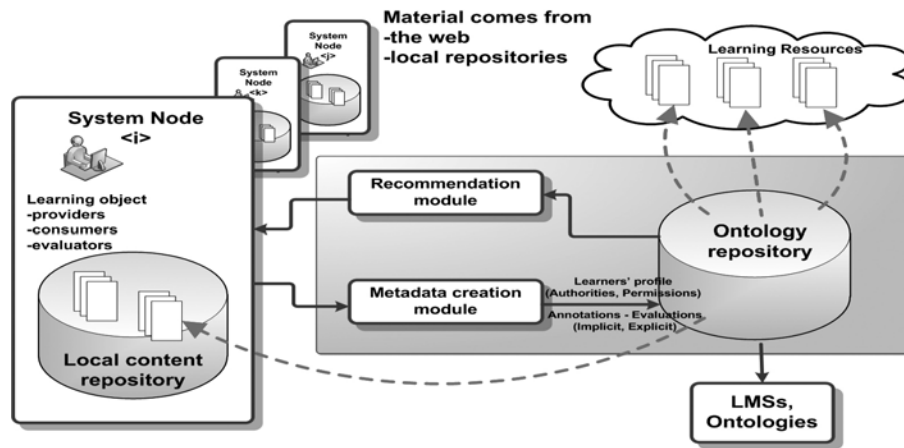
3.2   The ontologies

The properties of the learner/learning resource are chosen from the PAPI/LOM entries by adding the prefix has, e.g., the PAPI entry 'Certification' is transformed to 'hasCertification'. The values to these properties are limited to the values of the relevant PAPI/LOM entries, thus, for the property 'hasCertification' the permitted values are {Vocational Training, Higher Education, MSc, PhD, Continuous Formation}. The concepts and the rules that govern this system are described using the knowledge representation language F-Logic. This was due to the F-Logic capability in representing the properties of a concept, as well as, in defining rules. F-Logic is also promoted by advanced ontological systems such as OntoStudio Engineering Environment (2008).

The ontologies designed to describe the concepts of the e-learning system are:

3.2.1   The learning resource ontology

The 'learning resource' is depicted using the concept $L = \{l_1, l_2, ..., l_m\}$, each l_j having l properties $l_jp = \{l_jp_1, l_jp_2, ... l_jp_l\}, \forall\, j = 1, ..., m$. The properties and their domains D consist of the corresponding data elements chosen from LOM. The definition for the learning resource, in F-logic, is:

```
LearningResource[title; learningResourceURI; description; author;
...
   hasClassification=>>LOM#Classsification [{H.5.1.1 Web Design
   Tools, H.5.1.2 Image Processing Tools, ...}],
   hasFormat=>>LOM#Format{doc,pdf,txt,wav,..,mp3,other};
   hasLanguage=>>LOM#Language{en, el, fr, it,...,de};
   hasInteractivityType=>>LOM#InteractivityType{Active,
   Expositive, Mixed};
   hasLearningResourceContext=>>LOM#ResourceContext{Vocational
   Training,
               Higher Education, MSc, PhD, Continuous Formation};
   hasLearningResourceType=>>LOM#LearningResourceType{Exercise,
         Figure, Book, Lecture, Tutorial, Paper, Diagram, Video,
         Audio, Presentation, Lecture, Simulation, Questionnaire,
         Graph, Index, Slide, Table, Narrative Text, Experiment,
         Problem Statement, SelfAssessment};
   hasInteractivityLevel=>>LOM#InteractivityLevel{Very Low, Low,
   Medium,High, Very High};

   hasSemanticDensity=>>LOM#SemanticDensity{Very Low, Low,
   Medium, High, Very High}
   hasDifficulty=>>LOM#Difficult{Very Easy, Easy, Medium,
   Difficult, Very Difficult};

   hasCoverage=>>LOM#Coverage{Very Low, Low, Medium, High, Very
   High}].
```

where # defines the namespace[1] of each ontology.

The resources that have the same values in their properties are considered as similar and can be proposed alternatively.

3.2.2 *The learner ontology*

The 'learner' (equally, 'consumer" for the rest of the paper) is denoted by the concept $C = \{c_1, c_2, …, c_n\}$. Each instance c_i of this concept has k properties, which is presented by the ordered vector, $cip = \{cip1, cip2, ...cipk\}, \forall\, i = 1,...,n$ describing his profile. Two specific properties 'hasUserRole' and 'hasIntendedUserRole' are proposed from LOM. The concept 'learner' in F-logic is described as follows:

```
Learner[name; learnerURI; age; login; password; hasWeight,
...
  hasCertification=>>PAPI#Certificate_list{Vocational Training,
  Higher Education, MSc, PhD, Continuous Formation},

  hasIntendedUserRole=>>

  LOM#IntendedEndUserRole{Lecturer, Learner, Trainer, Trainee};

  hasUserRole=>>LOM#UserRole{Beginner,Pro-Intermediate,

  Intermediate,Post-intermediate,Advanced};

  hasPreferredLanguage=>>LOM#Language{en,el,fr,de,...,it};

  hasPreferredFormat=>>LOM#Format{pdf,doc,wav,avi,...,txt};

  hasLearningStyle=>>PAPI#LearningStyle{sensing/intuitive,
  active/reflective, visual/verbal, sequential/global};

  hasDownloaded=>>[PAPI#Performance.learning_experience_
    identifier=>>

  learningResourceURL];

  hasReputed=>>[PAPI#Performance.learning_experience_
    identifier=>>

  learningResourceURL];

  isSimilarTo=>>Learner::learnerURL;
  ].
```

The learners' properties and their values are attached a weight that have been chosen according to their significance. An instance of them is shown in Table 1.

Table 1   The correspondence of the learner properties to arithmetic values

Property name	Domain	Allowed values
cp1 = hasCertification, weight = 0.9	PAPI: Certification	{Vocational training: 0.3, continuous formation: 0.4, higher education: 0.6, MSc: 0.7, PhD: 0.9}
cp2 = hasUserRole, weight = 0.5	LOM: UserRole	{Beginner: 0.1, pro-intermediate: 0.3, intermediate: 0.5, post-intermediate: 0.7, advanced: 0.9}
cp3 = hasIntendedEnd UserRole, weight = 0.9	LOM: IntendeEndUserRole	{Lecturer: 0.8, trainer: 0.5, learner: 0.3, trainee: 0.2}
cp4 = hasPerformance, weight = 0.7	PAPI: Performance	Is calculated
cp5 = hasPreferredFormat, values {0, 1}	LOM: Format	{doc, pdf,wav, mp3, txt}
cp6 = hasPreferredLanguage, values {0, 1}	LOM: Language	{en, el, fr, it, de}

Finally the relationship 'isSimilarTo' is defined to connect the URI of a single learner to a set of URIs of other 'similar' learners. The similarity between learners will be defined later in this article.

3.2.3   The reputation ontology

To further facilitate the selection of the most suitable LRs, apart the LOM and PAPI description metadata, evaluation metadata from learners about the resources is also collected. This metadata is maintained in a third ontology – a so-called reputation-ontology (Kerkiri et al., 2006). The instances of this ontology connect the two concepts, namely the LRs and the learners. The instances of the reputation ontology are attached as an additional value to the LR. Bi-directional linking between the URL where the resource is located and our data repository makes the cumulative reputations of the resource available in public. The content of this evaluation ontology derives from the usual behaviour of the users of collaborative systems who tend to share their opinions about items they consumed. This enhances the participation of the learners in the educational process.

The first concept of the reputation ontology is the 'evaluation criteria'. Several criteria can be used depending on the educational topic and the scope of the course. E.g., in Massachusetts recommended criteria for distance learning courses (2003), a great range of them can be found. As an example, the evaluation criteria for a paper usually are clarity, originality, significance, novelty etc. Apart the content of the resource, evaluations can also be collected for a number of the descriptions of the LR – thus, depicting the opinion of the learner for the description metadata of the resource. Evaluation upon description metadata may unveil inconsistencies between the description metadata and the actual content of the learning material and their adoption may lead to more accurate descriptions. Such descriptions are indicatively the semantic density, the difficulty, the interactivity of the LR etc. In our system a variety of evaluation parameters are combined to conclude in a final result. In such cases each parameter has to be evaluated individually. But it seems difficult for a learner to answer in numerous questions about a number of features for the LR he has consumed. Thus, we chosen as a criterion the 'overall quality' of the resource that represents all the parameters engaged in the evaluation.

For this criterion the leaner is asked to select one among a set of available values of the Likert[2] scale (very low, low, medium, high, very high). The verbal value of the Likert scale must be correlated to a decimal one in order to participate to calculations. The correspondence between the two scales used in the system is shown in Table 2.

Table 2   The correspondence of Likert scale to the decimal indicatively for the property difficulty

Property	Corresponding search width	Mean weight
Very easy	[0–0.20] (width 0.21)	0.105
Easy	[0.21–0.42] (width 0.21)	0.315
Medium	[0.43–0.58] (width 0.16)	0.5
Difficult	[0.59–0.79] (width 0.21)	0.695
Very difficult	[0.80–1] (width 0.21)	0.895

When Likert scales are used, the medium-value choice (value 'medium' in our scale) is often selected by a user when he does not want to express his opinion. To moderate this phenomenon a narrower width is assigned to the medium value. As one may notice a similar scale can be used when a learner characterises specific properties of the LR having a scalable value. Such properties in our system are: `hasDifficulty`, `hasInteractivityType`, `hasCoverage`, `hasSemanticDensity`, `isForUserRole`. The values of each LOM/PAPI property are the values of this evaluation. The F-Logic representation of this concept is:

`ReputationCriteria[weight;hasReputationForTheOverallQuality;].`

A second concept of the reputation ontology is the 'explicit evaluation' of a learner, $ER = \{er_1, er_2, …, er_q\}$. This concept collects explicit reputations for a specific learning resource l_m from a specific learner c_i. An instance of this concept is of the form $er_m = (c_i, l_m, value)$. Each of the instances of the ER concept combines the URIs of the two concepts LR and Learner. Two new relationships, 'isFromLearner' and 'isForlearningResource', are defined that connect the ontologies. To show that a learner has evaluated a resource the property 'hasReputed' is defined. Its F-logic representation is:

```
ER[value; isFromLearner:Learner.learnerURI;

   isForLearningResource:LearningResource.learningReourceURI;

   isForCriterion:ReputationCriteria.rpi;

   value;]
```

The third concept of the reputation ontology is $IR = \{ir_1, ir_2, ..., ir_3\}$. It collects the 'implicit evaluations' for the LRs. An instance of this concept is created when a learner downloads an LR but he does not provide an evaluation for it. An instance of this concept is of the form $ir_m = (c_i, l_m)$. To show that a learner has attached a learning resource to his profile without evaluating it, the 'hasDownloaded' property is defined. Its F-logic representation is:

```
IR[value;

    isFromLearner:Learner.learnerURI;

    isForLearningResource:LearningResource.learningReourceURI

].
```

The URIs of the resources a learner has 'evaluated', or 'downloaded' are instances of the concepts ER and IR, and are both connected to the PAPI property `PAPI#Performance.learning_experience_identifier` of the learner. The intersection of the ER and IR sets of the learner is the null set, and their union is the `PAPI#Performance.learning_experience_identifier` set.

Figure 2   The graphical representation of the three ontologies and their relationships (see online version for colours)
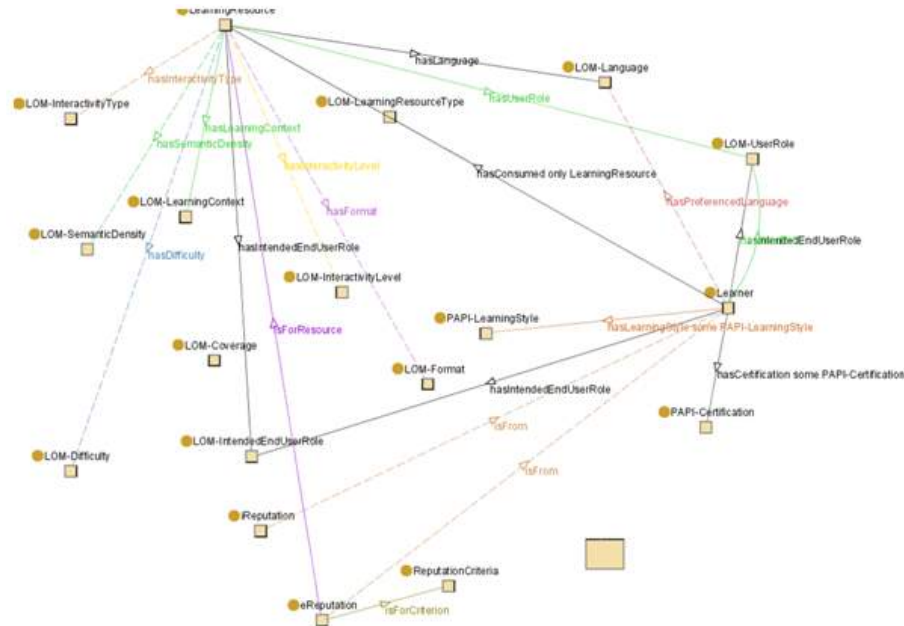
Part of the ontology is depicted in Figure 2.

4   Retrieve and recommend

In the semantic-web technologies the retrieval is implemented using queries that handle the items' properties. For example, in SPARQL W3C Recommendation (2008), a query that finds the title and the author of 'difficult' LRs about 'masks' in 'Photoshop' is expressed as:

```
PREFIX lom:
  <http://ltsc.ieee.org/wg12/files/LOM_1484_12_1_v1_Final_Draft>
PREFIX reputation: <http://www.uom.gr/e-learningOntology>
SELECT ?title ?author
WHERE { { x? title like 'mask' and LOM:Classification =
  'H.5.1.2.1' and
lom:Difficulty = 'difficult'. }}
```

The most obvious way to propose a resource is to promote the top evaluated one. This LR though may not always be the most appropriate for the learner, because the evaluation it has acquired comes from learners of different profile, e.g., evaluations that come from 'advanced' learners for the 'difficulty' of an LR perhaps are contradictive to the opinion of a 'beginner' learner. Thus, the evaluations for the same feature have to be further explored. As per this paper, a hybrid retrieval system and a recommendation

methodology is proposed. The proposed retrieval-recommendation module of our e-learning system is feed with metadata about the learning resources, the learners and their evaluations, along with the rules of the ontologies. The values of the learners' properties are extracted and their vectors, containing the values of their properties, are created. The evaluations are also extracted and accumulated. For each leaner c_i two kind of sets are created:

a LIR_i, LER_i, that contain the LRs that c_i has attached to his profile, using the 'hasReputed' and 'hasDownloaded' properties, accordingly

b   the sets $LCcommon_i$ that holds the LRs that each learner being on a neighbourhood according to his properties has downloaded and $LERcommon_i$ that contain the LRs the learners of the same neighbourhood as learner c_i have evaluated.

Figure 3   The proposed retrieval model
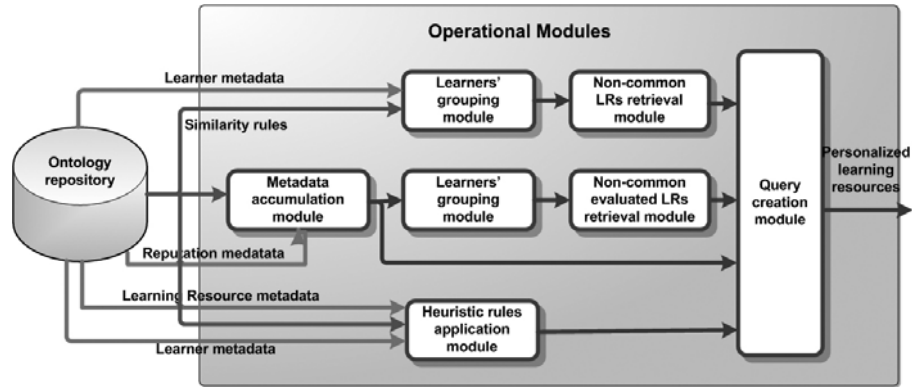
The functionality of each module presented in Figure 3 is explained below.

4.1   Learners' grouping according to their properties

Using the corresponding weights of Table 1 for the properties of the learner c_i the vector $c_i p = \{c_i p_1, c_i p_2, ..., c_i p_k\}$ can be described using arithmetic values. E.g., if the property vector of the learner c_i is $c_i p = \{hasCertification, hasUserRole, hasPerformance, hasIntendedEnduserRole\}$ and the values he had acquired to these properties are $c_i p = \{Msc, Advanced, 0.7, Lecturer\}$, then the vector representing his properties can equally be substituted by the weights of these properties, $c_i p = \{0.7*0.3, 0.9*0.2, 0.7*0.3, 0.8*0.2\}$. The total weight of each learner is the sum of the products of the weights of his properties multiplied by the total weight of the property (formula 1). To normalise the different kind of learners in the total number of learners, the term frequency-inverse frequency model is applied.

$$w_{ci} = \sum_{q=1}^{t} w_{iq} * w_q / \sum_{q=1}^{t} w_q \tag{1}$$

where w_{ci} is the total weight of learner c_i, w_{iq} the weight of the value of his properties and w_q the weight of the property. This weight multiplies each of the c_i evaluation.

A second possibility of this correspondence is that the vector space model (VS) can be used to calculate the similarity between them. According to the VS model the similarity between two vectors is calculated by the inner product of their values (formula 2):

$$f(c_i, c_j) = sim(c_i, c_j) = \frac{\vec{c}_i * \vec{c}_j}{|\vec{c}_i| * |\vec{c}_j|} = \frac{\sum_{k=1}^{t}(w_{i,k} * w_{j,k})}{\sqrt{\sum_{k=1}^{t} w_{i,k}^2} * \sqrt{\sum_{k=1}^{t} w_{j,k}^2}} \tag{2}$$

w_{ik} is the vector of the weights of the k properties of learner c_i and, similarly, is w_{jk} for learner c_j. The closer the result to 1 is, the stronger the correlation between the learners c_i, c_j.

Similarity between learners is calculated using algorithm 1:

Algorithm 1   Learners' similarity according to their properties

---

Step 1:   for each learner c_i of the set C

   Calculate his similarity to any other learner c_j, $j \neq i$, using formula (2)

Step 2:   A threshold is calculated to allow a divergence to the learners' similarity. This threshold derives from the pairs of similarities of Step 1, using formula (3)

$$threshold_p = \sum_{i=1}^{n} \frac{\sum_{j=i+1}^{n}(1 - f(c_i, c_j))}{n-i} a, c_i, c_j \in C, i, j \in \{1,..,n\} \tag{3}$$

Step 3:   //This step finds a neighbourhood, using the threshold

   Step 3.1:   Set $r = 1$

   Step 3.2:   Create the first similarity set $Csimilar_r = \{\}$

Step 4:   insert the instance c_i into the set $Csimilar_r = \{c_i\}$

   $C = C - \{c_i\}$

Step 5:   for each $c_j, j \in C, j = i+1,...,n$

   if $f(c_i, c_j) \leq threshold_p$ then

   $Csimilar_r = Csimilar_r + \{c_j\}, C = C - \{c_j\}$

Step 6:   if $C \neq \{\}$ then $r = r + 1$, goto Step 1, to create the next similarity set

where $\cap Csimilar_r = \{\}$, $\cup Csimilar_r = C, r = 1,..,q$, ($q$ being the number of the similarity sets) have been created from this algorithm.

//Next step finds the set of the common resources of the learners of each neighbourhood

Step 7:   for each learner c_i of the set C,

   Step 7.1:   using the property 'hasDownloaded', his instances l_j $ir_i = (c_i, l_j)$ of the set IR are found

Step 8:   for each set $Csimilar_r$, let $LCcommon_x$ be the union of resources of all its learners,

   Step 8.1   for each learner c_i of $Csimilar_x$ //the LRs of his neighbourhood is found

      Step 8.1.1:   the intersection of the two sets $LIR_i \cap LCcommon_r$ is created

---

This algorithm groups the learners according to their properties and finds the sets of the LRs he and his neighbors' consumed but they did not evaluate. This similarity is depicted using General rule 2 which, in F-logic, is defined as follows:

General rule 2

```
FORALL Ci:Learner, Cj:Learner,

Ci[isSimilarTo → Cj] ← [lessOrEqual(f(ci,cj), threshold_p)].
```

Similarity between learners leads to the result that they can be proposed the same LRs.

4.2   Learners' grouping according to their evaluations

A second method that finds similarity between the learners is by examining their opinions about common consumed LRs. Similarity between their evaluations anticipates that is very likely for these learners to meet again in the future. To calculate the dependence between the evaluations of two different learners the Pearson's correlation is used. Thus, the similarity $f(er_i, er_j)_q$ of the two learners c_i, c_j is (formula 4):

$$f(er_i, er_j) = \frac{\sum_{m=1}^{p}(w_{ci}*er_{m,i}-\overline{er_i})*(w_{cj}*er_{m,j}-\overline{er_j})}{\sqrt{\sum_{m=1}^{p}(w_{ci}*er_{m,i}-\overline{er_i})^2}*\sqrt{\sum_{i=1}^{p}(w_{cj}*er_{m,j}-\overline{er_j})^2}} \tag{4}$$

where p is the common evaluated LRs by the learners c_i, c_j, w_{ci} is the weight of the learner c_i, $er_{m,i}$ is the evaluation that learner c_i for a specific learning resource l_m, $\overline{er_i}$ is the average value of the reputations of c_i for the set of p common evaluated LRs. The same holds for learner c_j. This formula combines the history of the evaluations of the two learners c_i, c_j and calculates the relevance between them. It does not include any information about the opinions of the learners for the learning resource under examination. It predicts that the learners' opinions may meet again. The Pearson's formula output belongs in the range [–1, 1], where –1 means that variables are completely independent, 0 they are neutral, and +1 means that they are fully correlated.

   To find out the similarity between learners, we assume that they have to evaluate a core subset of the learning resources. This means that they have studied at least the basic concepts of a course. Otherwise the formula (4) has to be calculated for a number of common sets of LRs that comprise of a very short number of resources which may not produce an actual similarity. After that the similarity according to their reputations is calculated according to algorithm 2:

Algorithm 2   learners' similarity according to their reputations

Step 1:	For each instance c_i, $i = 1, .., n$, of the set C,
	using the property hasEvaluated,
	find the triples $er_i = (c_i, l_j, value)$ of the set ER and create the set LER_i
Step 2:	for each instance c_i, $i = 1, .., n$, of the set C,
	Step 2.1 check if LER_i is a subset of the obligatory LRs
	if not the learner c_i is out of the rest of the process
	else the learner is inserted in the set SC, (the learners that have evaluated the core resources)
Step 3:	for each pair of learners of the set SC calculate the formula (4)
Step 4:	using the output of the formula (4) for each of the pairs ci, cm, $i \neq m$, calculate the threshold as follows:

$$threshold_{er} = \sum_{i=1}^{p} \frac{\sum_{m=i+1}^{p}(1 - f(er_i, er_m))}{p - i}, c_i, c_j \in SC \tag{5}$$

Step 5:	set $r = 1$, create the set Sr – the first neighbourhood
Step 6:	attach randomly the learner c_i in Sr and remove him from the set of learners C
	Step 6.1: for each $c_m \in Sr$
	if $f(c_i, c_m) \leq threshold_{er}$ then
	$Sr = Sr + \{c_m\}$ and $SCr = SCr - \{c_m\}$
Step 7:	if $SC \neq \{\}$ then $r = r + 1$ and goto Step 1 to create the next neighbourhood
Step 8:	for each learner c_i of each Sr
	Step 8.1: find the instances of the LRs using the property 'hasReputed'
Step 9:	find the intersection $LERcommon$ of the LRs of the learners of the neighbourhood r, and the set LER_i

This algorithm groups the learners in pairs according to the evaluations they provided. It also constructs the sets of the LRs that learners in pairs evaluated in common. The similarity between learners that is based on the similarity of their evaluations is depicted using General rule 3 which, in F-logic, is defined as follows:

General rule 3

```
FORALL Ci:Learner, Cj:Learner,

   Ci[isSimilarTo → Cj] ← [lessOrEqual(f(eri, erj),
   threshold_er)].
```

4.3   Learners' grouping according to learning style outcomes

A final possibility to correlate learners and learning resources comes from ontology alignment. Curino et al. (2007) define the ontology mapping/alignment as 'the process of bringing two or more ontologies into mutual agreement, by relating their similar concepts and roles by means of some kind of mappings, and making them consistent and coherent'. Generally, ontology mapping methods can be categorised into two approaches,

the concept-based approach and the instance-based approach. Concept-based approaches are top-down approaches, which consider concept information such as name, taxonomies, constraints and relations and properties of concept elements for ontology merging. On the other hand, instance-based approaches are bottom-up approaches, which build up the structural hierarchy based on instances of concepts and instances of relations. In our system we follow the second approach.

Table 3   Learners' properties affected from the learning style vs. learning resources' properties

Learning style	Learning resource properties	Learning style	Learning resource properties
Sensing	Experiments,data, facts, LRs having high interactivity	Intuitive	Pictures, diagrams, flow charts, primitives, concepts, theories, LRs with high semantic density
Visual	Book, printings, diagrams, flow charts, videos, avi, presentations, time lines, demonstrations, films	Verbal	Case studies, experiments
Deductive	Books, diagrams, presentations	Inductive	Text, books, pictures, videos, avi
Active	Experiments, tutorials, questionnaires	Reflective	Paper, books, self-assessments
Sequential	Books, flow charts, algorithms	Global	Maps, pictures, novels

Table 4   Learner properties vs LRs' properties that aid to the ontologies' alignment

| Properties deriving heuristic rules based on learning style		Properties having common domains	
Learner property	*Learning resource property*	*Learner property*	*Learning resource property*
hasUserRole: 0.55	hasDifficulty: 0.25	hasUserRole	hasDifficulty
hasIntendedEnd UserRole: 0.45	hasInteravtiviytLevel: 0.20	hasPreferredLanguage	hasLanguage
	hasFormat: 0.20	hasCertification	hasLearningResource Context
	hasLearningResourceType: 0.20		
	hasSemanticDenstiy: 0.20		

A possibility to correlate several properties of the two ontologies comes from pedagogic theory. Felder and Silverman (1998) concluded that learners having specific learning style have better performance results if the material provided to them has specific properties on specific characteristics. The Felder-Silverman model defines several learning types which they are presented in Table 3.

As seen from this table researches (Ahn, 2003) concerning the conjunction of several characteristics of the learning resources and the characteristics of the learners, concluded e.g., that intuitive students prefer lectures and less interactive learning resources while sensing e-students prefer learning objects with high interactivity level and case studies. Format 'video' or 'avi' suits better to 'visual' learners, while learners having style 'sensitive' are connected to LR property 'semantic density' and format 'tutorial'. The properties that derive from the learning style theory are shown in the first two columns of the Table 4.

As there are contradictive opinions about the effect of leaning style on the educational process, these properties participate using a weight. The total weight of each learner property weight defines its importance. An indicative instance of these weights is shown. Finally, as seen from the description of the two ontologies, Learner and LR, some of their properties have common domains, e.g. language, format etc. These properties depicted in the last two columns of this table contribute with a value of 1 or 0, depending on their existence. Let's notice that the "Format" property was not supposed to be one of the learner preferences because it is investigated under the impact of the learning style.

The alignment of the ontologies is shown in Figure 4.

Figure 4   Alignment between the ontologies
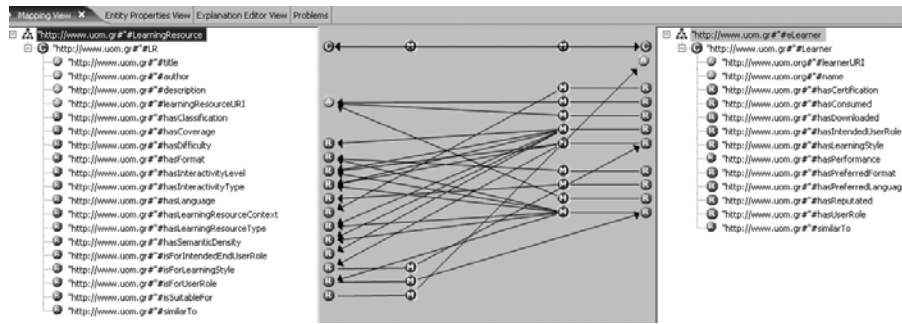
The mapping between the ontologies is implemented though the alignment of the values of the properties they have in their instances, using a rule, the general pattern of which, in F-logic, is:

General rule 4

```
FORALL C:Learner, LR:LearningResource

    LRi[isSuitableFor → Cj]

← Cj[(@learnerProperty(@Vi)) AND
LRi[(@learningResourceProperty(@Vj))

].
```

Instances of this rule are created replacing the property-variables with the properties shown in Table 3. V is chosen from the set of the available values of these properties. Examples of this rule are:

Example 1

```
FORALL LR@LearningResource, Cj:Learner,

    LRi[isSuitableFor → Cj]

← Cj[hasLearningStyle → active] AND LRi[hasInteractivityLevel
→ high].
```

Example 2

```
FORALL LR@LearningResource, Cj:Learner,

  LRi[isSuitableFor → Cj] ← Cj[hasLearningStyle → Visual] AND

    (LRi[hasLearningResourceType->>{Tutorial, Simulation,

    Example} OR

      hasFormat->>Video]

  ].
```

Our recommendation method reorders the results of a traditional search method. The LRs found from a leaner's query (this anticipates that match the criteria of the learner) are revealed to him according to the following scenario: first the set of the LRs that have accumulated positive evaluations of learners are revealed, after that, follow the LRs that have been used by learners having similar profile to the one that submits the query, then, any other resource that matches the learner's criteria and does not belong to any of the above categories follows.

Observing the results of each step of this algorithm we shall notice that the learners belonging in the same neighbourhood were provided the same resources for the same queries. After that, the code that re-orders the retrieved LRs according to the proposals of the learning style computation filters the results of each step.

The results of the query the learner c_i asks to the system are filtered according to the following algorithm:

Algorithm 3   learning resources recommendation

The learner's profile c_i is known to the system

Step 1:   The learner c_i defines his criteria V and asks his query

The system returns the set *Lquery* of documents

Step 2:   for each l_j of the *Lquery* set

//this means that the LR fulfils the criteria of the learner,

Step 2.1:   compare each property l_jp_t of l_j, $t = 1, ..., l$, to each of the k learner properties $c_ip = \{c_ip_1, c_ip_2, ...c_ip_k\}$ using Table 4

Step 2.2:   if they are combined, then calculate formula (4):

$$l_{jweight} = \sum_{m=1}^{l} \sum_{t=1}^{k} w_{c_ip, m} * w_{l_jp, t} / \sum_{t=1}^{k} w_{l_jp, t} \tag{6}$$

Algorithm 3   learning resources recommendation (continued)

Step 3:   for each l_j of the *Lquery* set

    Step 3.1:   for every learner c_m of the set *LERcommon$_{i, m}$* of his ER neighbourhood

          check if l_j is in the set $LERm \cap LERcommon_{i, m}$

          if l_j is in $LERm \cap LERcommon_{i, m}$

             and the reputation value >= 'medium' then

//this means that the similar learner c_m has already consumed it and he is satisfied from it

          set the precedence of the LR to 1

Step 4:   if there are still LRs in the *Lquery* set

    Step 4.1:   for each l_j in the *Lquery* set

        if lj is in the $LIRi \cap LCcommon_r$

//this step finds if the l_j was consumed by learners that are similar to c_i according to properties of their profile

        set the precedence of the LR to 2 //explicit feedback is of greater importance

    Step 4.2:   eliminate the l_j from the retrieved LRS, $Lquery = Lquery - \{l_j\}$

Step 5:   if there are still LRs in the *Lquery* set

    set the precedence of the LR to 3

        eliminate the l_j from the retrieved set of LRS, $Lquery = Lquery - \{l_j\}$

Step 6:   reveal each l_j of the retrieved LRs in a descending order according to the precedence and the weight that were calculated from the previous steps

---

5   Implementation and evaluation

To test the proposals, a prototype system was set up. Initially, the ontologies, along with their relationships and rules, were implemented. The repository annotation phase of this system was implemented using the RDF/OWL infrastructure of KAON2. As Broekstra and Kampman (2001) mentioned, the implementation of the storage methods used to implement the semantic web technologies is irrelevant to the actual storage system. Plain text, rdf/owl files, rdbms, oo-dbms, etc., can be used identically and all these storage and access methods as well as the implementation schemes are equivalent. Custom java code handles the properties of the resources and the learners and implements the formulas and the algorithms. A GUI has been developed which implements an SQL-mediator of the SPARQL query that retrieves resources based on their metadata.

A great effort was made to feed the repository with LRs in a variety of alternative characteristics (e.g., a video presentation, a step-by-step presentation, a power point presentation, an html page, an image, a narrative text, an interactive document etc.) for the same learning subject.

An important evaluation parameter for a learning system would be the increase of the performance of its participants. There are many factors, though, that influences the performance of a learner apart the selection of the suitable material. Consequently, the goal of our evaluation was to calculate the influence of our algorithm on the semantic

accuracy of the retrieved LRs. To end up with a result, queries using only description metadata were examined against to queries that combine both description and reputation metadata. Both queries evaluated according to their precision versus the total recall (Davis and Goadrich, 2006).

The evaluation procedure was facilitated by the fact that the recall was known to the system as we had a limited amount of resources. The results from the first kind of queries were compared against the results from the second one. As it was expected the first kind of queries returned the same results for each learner. The second kind of queries re-ordered depending on the learner that submitted the query. Trials proved (Figure 5) that the second type of results had a greater relevance to the learners' requirements. As seen from this diagram the satisfaction of the learners from the first set of of LRs was also high. This was due to our initial effort to feed the repository with qualitative resources.

Figure 5 Precision-recall results (see online version for colours)
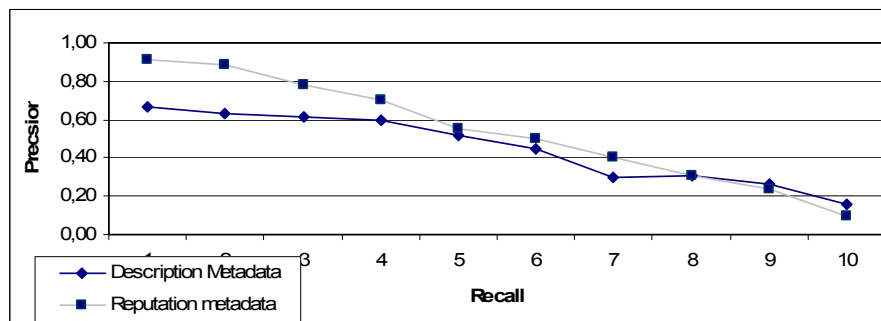
A parameter of our evaluation was the magnitude of relevance of the results found on the top of the list. As it was proven from a second set of questionnaires, the first six learning resources sufficiently satisfied the educational needs.

Figure 6 The magnitude of the relevance of the resources (see online version for colours)
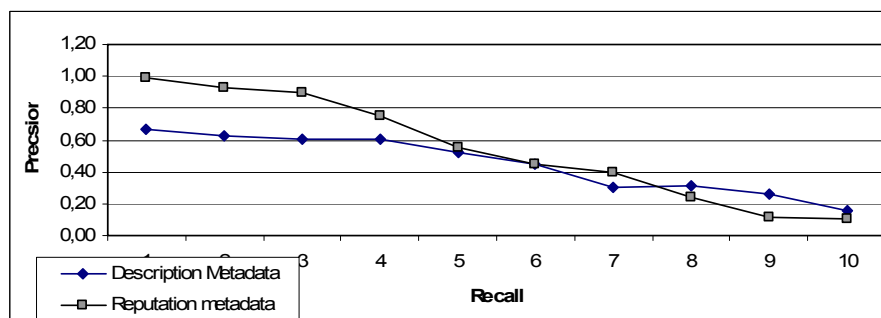
The evaluation proved that the learners found the magnitude of the relevance of the first 4 LRs stronger. The results of this evaluation are shown in Figure 6. It was a proof that the learning style is a factor that in some cases increases the learning outcomes of the

educational process. A result of this latter approach was that alternate LRs were promoted to each learner and after a while the set of the positive evaluated resources increased.

In our future plans is the enhancement of the ER concept with the URI of the criterion about individual characteristics of the LRs (such as semantic density, interactivity etc.) to conclude to an indicator about the characteristics of a desirable LR for this course. Our focus in a next evaluation is the deeper examination of the impact of the learning style in the recommendation algorithm. To do so we intend to examine a greater variety of the weights of the characteristics of the LRs Table 4. Finally, there is a lot left for future research so that to enrich the design of personal spaces adjusted to each particular e-learner in personal learning environments (Chatti et al., 2007) with the required social aspect of learning by means of connecting each personal space to other personal spaces for effective knowledge sharing.

As a conclusion from the whole effort proved that the learner would have to examine much less retrieved resources in order to filter those that are suitable to his informational needs. Furthermore, these learning resources have a greater impact to his profile. In our future plans is the expansion of the data pool to contain a wider categorisation of LRs and the examination of a wider range of learners' attitudes, (e.g., demographic, etc.). Within a learning environment where learner needs are taken into consideration the potential for enhanced participation is generated (Vivitsou et al., 2007) therefore the outcome of such an effort may offer new options to the instructional learning strategy.

6   Conclusions

In this paper an e-learning system is proposed that is based on semantic web-based methods. In this system, the learners' feedback, expressed as reputation metadata, is used to propose suitable LRs', through recommendation techniques. Ontologies' are designed based on educational standards to implement the entities of the system. The alignment of the ontologies, based on properties that derive from learning style, offers a greater opportunity for personalisation. The ontological approach is a broadly accepted basis for the implementation of a widely accepted system. The first conclusion from this research is that the reputation metadata increase the satisfaction of the learner from the document retrieval. Our results proved that the reputation metadata fetches more accurate learning resources to the query-criteria and increases the learner's satisfaction from the retrieved learning objects.

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Notes

1   A 'namespace' is an abstract container or environment created to hold a logical grouping of unique identifiers (i.e., names).

2   http://ourworld.compuserve.com/homepages/jsuebersax/likert.htm.