

Towards Personalized Adaptive Learning in e-Learning Recommender Systems

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Abstract—An adaptive e-learning scenario not only allows people to remain motivated and engaged in the learning process, but it also helps them expand their awareness of the courses they are interested in. e-Learning systems in recent years had to adjust with the advancement of the educational situation. Therefore many recommender systems have been presented to design and provide educational resources. However, some of the major aspects of the learning process have not been explored quite enough; for example, the adaptation to each learner. In learning, and in a precise way in the context of the lifelong learning process, adaptability is necessary to provide adequate learning resources and learning paths that suit the learners' characteristics, skills, etc. e-Learning systems should allow the learner to benefit the most from the presented learning resources content taking into account her/his learning experience. The most relevant resources should be recommended matching her/his profile and knowledge background not forgetting the learning goals she/he would like to achieve and the spare time she/he has in order to adjust the learning session with her/his goals whether it is to acquire or reinforce a certain skill. This paper proposes a personalized e-learning system that recommends learning paths adapted to the users profile.

Keywords—e-Learning; adaptive learning; recommendation system; ontology

I. INTRODUCTION

With the broad coverage of the internet, access to learning content through the web has become increasingly easy. A variety of educational systems such as MOOCs¹ [1] have emerged, with an essential mission that is provide educational content, to learners willing to learn; yet the diversity of people implies that each learner has her/his own particular preferences, knowledge and competencies. In that perspective adaptability was a major and essential criteria to add to e-learning systems providing learning resources, to make learning content suitable to learners. This adaptation takes a process that is established in many levels. At the cognitive model level as Ruiz et al. [2] propose, it have to go through the following steps:

- to classify the user by choosing a suitable learning style;
- to present adaptation to system by developing good techniques then conceive that adaptation to suits the user's preferences;

- choosing the right technologies and realization of that adaptation on a computer.

Brusilovsky and Millan [3] on the other hand put focus on the user modeling inside an adaptive system where the user information are a distinctive aspect to consider when the system intervene. The interaction of the user should be noticed with attention, when she/he searches, navigates; but also her/his interest, knowledge, background, learning style, goals, etc. The priority should be given to the content suitable to what user interest in the most. User modeling featured-based or stereotype-based [3] should either way take into consideration the personal information of the individual. A definition of adaptation is the reconfiguration of entities in order to adjust them to a certain request. It can be categorised as the following according to [4]:

- *Machine Centred*: In this case, the learning process is guided by a series of actions from user and analyzed by her/him.
- *User Centred*: The learning resources (lessons) are personalized by learners themselves as stats [4].

Underneath these categories we find several kinds of adaptation [3], [4]. We mention:

- *Adaptation of Content/Adaptive Evaluation*: The content of activities and resources are faced to dynamic change.
- *Adaptation of Visual Presentation*: It represents mainly the components of an interface and their properties, how and where they are displayed.
- *Adaptation of Learning Process*: The learning process is dynamically modified to the manner in which the courses contents are provided in suitable ways.
- *Adaptive Information Filtering*: The system takes care of suitable information retrieval in order to give relevant results to user.
- *Adaptive User Grouping*: This allows a distant learners to collaborate and provide assistance in achieving specific tasks.

However we could not talk about adaptation in a system without mentioning personalization which according to [5] is included into a simple mechanism that need specific technologies to ensure accurate results. Adaptation inside a system

¹Massive Open Online Courses

takes multiple parameters. The most important one, and regardless of the technique used, is the user profile and information; taking into consideration that the user interest and motivation are what will keep her/him continue learning. Therefore well modeling her/his profile is essential. This profile is a personification of different features of user. We note this profile can be built from two types. The first one constitutes a general profile not specific to any user characteristic. The second one is the developed version of the former. After extracting the user information, a personalized profile is created to represent her/him. This study provides a critical overview of previous research related to adaptive recommender systems in e-learning field. Mainly we seek to answer the following research questions:

- What aspect of adaptation should be enhanced and why?
- How is adaptation implemented in recommendation systems?
- How to enhance it?

This paper is organised as follow: Section II will outline similar research work papers. Then in Section III we will underline common techniques and methods used for adaption in adaptive e-learning systems. Section IV presents a comparison about different adaptive systems. Their advantages and drawbacks are highlighted. Section V details our proposition, then in Section VI, we make a position from the current research tendency in e-learning adaptive recommender systems and their techniques, which further consolidates our proposition in the previous section. Finally, Section VII concludes this paper and presents some perspectives.

II. ADAPTIVE E-LEARNING SYSTEMS

Many studies have been conducted in the field of adaptive e-learning systems. In this section, we present an overview of the research papers selected from the literature review. We mention most relative ones from 2017 to 2021. This selection was based on the relevance and the level of the adaptability in e-learning systems in terms of adaptive information filtering, adaptive user profile and adaptive users group. The process of selection was made as follows: among many articles found in Google scholar, ResearchGate², DBLP³ while searching for keywords such as “adaptation in e-learning systems”, “recommendation techniques”, “adaptative systems”, etc. 26 papers were selected based on their relevance, their accuracy, and the number of citations in others research works. Of these 26 articles, we have selected seven (7) to be mentioned, based on the year of publication and direct projection of their content on our research.

Almmouhamadi et al [6] present a survey on the rising techniques of adaptation in educational adaptive systems. They emphasize the two most used techniques of data mining in AI: (i) the predictive which is a prediction of the next tag in general. By selecting a predictor variable or group of variables, these techniques are applied to extract single or multiple variables with predicted values; it is about predicting

a missing or unknown item of a dataset, and ii) the descriptive (clustering) one which is based on grouping similar objects. The primary uses of clustering are to segment or categorize (e.g., sorting customer data by age, occupation, and residence) or to extract knowledge in an effort to find subsets of data that are challenging to categorize. This method is about determining a class for an element in a dataset. For instance, we can think of prediction as anticipating the appropriate course of treatment for a certain disease in a specific individual. Whereas the grouping of patients based on their medical records can be considered classification.⁴

George and Lal [7] show how ontology-based recommender systems became an emergent research way in the e-learning field. Those systems address most of issues found in e-learning recommender systems. Giving personalized recommendations to learners is one of the practical applications of employing ontology-based recommender systems. Based on the learner’s interests, goals, etc., the recommendations that are given to them become precisely relevant. As a result, the learner is encouraged to finish what she/he started. They illustrated their point of view after a study on research papers published during the last decade concerning the recommender systems in e-learning. They present extraction and modeling techniques used and compare existing recommender systems in e-learning in the scope of these techniques. From another perspective Eke et al. [8] focused on user profiling methods, and the challenges such as multi-dimensional representation, privacy of user’s information, cold start problem for new users, temporal behaviour of individuals, limitation of interest, etc. They also discuss the most relevant solution for those challenges such as ontology representation and general purpose profile, and so on.

In [9], Nabizadeh et al. outline the personalization methods and illustrate the challenges facing those methods, and how to improve the existing personalization techniques. Zaoudi et al. [10] present a critical research paper on existing approaches used in learning scenarios and adaptive e-learning situations.

Then Javed et al. [11] present review of a widely used methods in recommender systems, context-based and content-based, and a hybrid method combining multiple methods in order to benefit of the advantage of each method to cover the disadvantages of each one. Just recently, Raj and Ranumol [12] provide a review of research papers on a period of time from 2015 to 2020, with critical study of adaptive recommender systems proposed comparing on one hand methods used in those systems, from the hybrid methods, content or agent-based, semantic web based, etc. On the other hand, they are also comparing the attributes such as the user content rating, learning style, knowledge level, etc.

Table I summarises our comparison of recent research works, which we analyse in Section IV.

III. RECOMMENDATION TECHNIQUES

Adaptive recommendation systems can be divided into knowledge-based, content-based, user-based or based on hybrid approaches. They can be categorised according to what the adaptation is based on and on the recommendation techniques

²<https://www.researchgate.net/>

³<https://dblp.uni-trier.de/>

⁴see classification-and-prediction-methods-in-data-mining

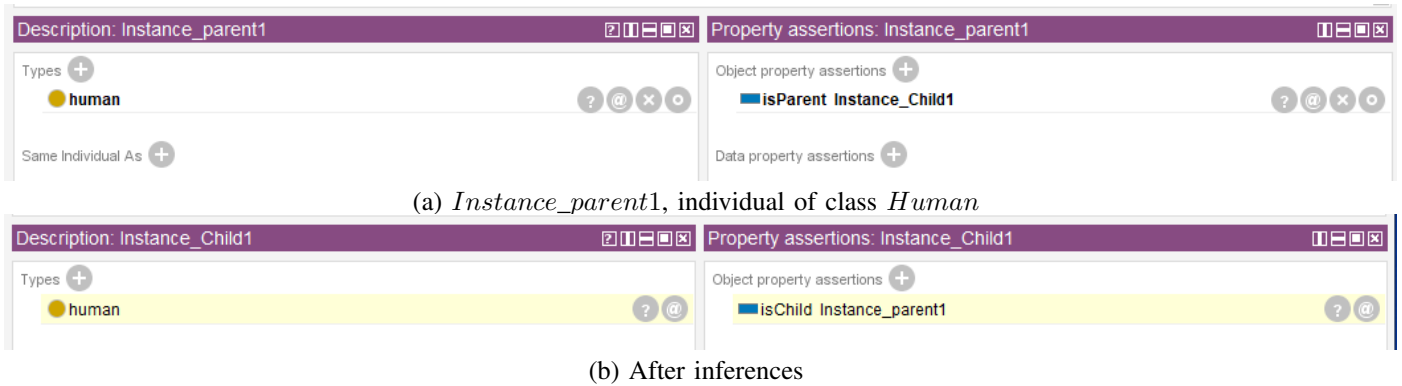


Fig. 1. Example of Inferred Knowledge by the OWL Reasoner HermiT.

used. Following those used techniques the adaptation can be based on:

- *User's Profile*: this method takes into account the characteristics of the user defined by her/his intrinsic characteristics, her/his preferences for the presentation of pedagogical resources to be recommended (text, audio, video, etc.), and the experience of other users with similar profiles. To do this, several techniques have been implemented to model user profile. This allows a learner model to be designed which, according to [13], is the representation of specific characteristics of a learner that may be relevant for a personalized interaction. Managing users' profile allows the user learning style to be predicted. Most of them are based on the widely used learning model "The Felder and Silverman Learning style Model" (FSLSM) [14]. It is worth noting that the learner model is not intended to be a representation of the learner's mental state but rather of the learner's characteristics such as personal information (age, gender, country, native language, etc.), cognitive traits, knowledge and skill levels, preferred learning styles, and personal preferences, such as cultural background, format of learning resources (text, audio, video, etc.), preferred language, etc. Munassar and Ali [15] and Aissaoui and Oughdir [16] propose a framework based on user profile modeling using ontologies, which represent the terminology (TBox) and assertions (ABox) such as instances of concept. From a knowledge base, a reasoner checks the consistency of the model and infer new knowledge depending of description logic level used [17].

For example, let us an ontology O (for didactic purposes):

```
Human(Instance_parent1)  
isParent(Instance_parent1, Instance_Child1)  
Human.isChild  $\equiv$  Human.isParent-
```

We can see below in Fig. 1 how the reasoner HermiT⁵ inferred new knowledge.

Fig. 1(a) shows an individual *Instance_parent1* of a class *Human* with a role (i.e. Object Property assertion in the editor Protégé⁶) *isParent*, which is the inverse role of *isChild*.

Fig. 1(b) displays, after starting the reasoner HermiT, new knowledge that has been inferred about *Instance_Child1* which belongs to class (noted *type* in Fig. 1) *Human*, represented in description logic by *Human(Instance_Child1)* and the new object property assertion *isChild(Instance_Child1, Instance_parent1)*.

- *Knowledge-Based*: this approach with slight similarity with the user profile based approach, in representing knowledge. It helps making recommendation by extracting information. In general, a reasoning system is behind that decision making, after having well represented knowledge.
- *Content-Based*: which is based on the content of the started themes. The evaluation of the content is done in an explicit way by the attribution of notes directly to the documents which represent the contents of the topics, or in an implicit way when the system estimates through user interactions the degree of relevance of a document [18].
- *Collaborative Filtering*: which is a widely used method that consists in projecting the preferences of an individual to a group of similar users. In other words, the recommendation is made on the basis of what our neighbors (users with similar profiles) have appreciated [19];
- *Social-Based*: basically these methods can be used to enhance an already existing system, by using social network to create similar groups [20]. One might assume that users who are friends on social networks can have a common interest, or even one user can be interested in a resources because her/his friends were or are interested in taking it. It would be interesting to detect the influencers. User activity on social-media also in recent years formed a good source for recommendation, the time she/he spends watching a video can give an idea on languages she/he understands, and the subjects that interest her/him. Furthermore the content she/he likes and comments or shares also are considerable source. Her/his geolocation history can also be known through her/his publications and the location she/he visits. A variety of information can be extracted through social networks.

⁵www.hermit-reasoner.com/

⁶protege.stanford.edu/

TABLE I. COMPARISON OF ADAPTIVE RECOMMENDER SYSTEMS IN E-LEARNING

Reference	KB	CB	UB	MU
Sarwar et al. [22]	X	-	X	hybrid techniques + ontologies
Agbonifo et al. [23]	-	X	X	collaborative filtrage + ontologies
Vagale et al. [24]	-	X	X	extraction form user model
Boussakssou et al. [25]	X	X	-	Q-learning
Shi et al. [26]	X	X	-	A designed knowledge graph + Bloom's taxonomy
Azzi et al. [27]	X	X	-	Automatic prediction of Learning style + Fuzzy C-means
El Fazazi et al. [28]	X	X	X	MAS+Q-Learning algorithm

- *Hybrid Methods:* they combine two or more approaches of the previous types of recommendation techniques [21]. For example, it can be based on user characteristics by modeling the learner's profile in the first step and, in the second step, recommending resources adaptively with respect to the profile. Usually the combination of these techniques aims to overcome the drawbacks such as the sparsity issue which is due to lack of user rating. Users are reluctant to give feedback on items they have tested. In addition to the sparsity, we mention the cold start problem faced by new users or new item. This issue shows up, when there is not a review/ratings of an item, making it unrecommendable despite its importance and relevancy. The same applies on new users. The difficulty of making recommendations based on a user's profile increases for new users with new profiles. Hybrid methods benefits of the advantages of each techniques used. However, some limitations still persist and even new challenges appear in hybrid approaches.

IV. COMPARISON OF ADAPTIVE RECOMMENDER SYSTEM

In this section, we compare adaptive recommender systems proposed firstly in terms of adaptability techniques used: Knowledge-based (KB), Content-Based (CB), User-based (UB) and Method-Used (MU);

and secondly in terms of adaptation itself, based on the two types mentioned in above Section I

Table I gathers recently proposed adaptive e-learning systems using different methods. We notice that [22], [23] are generally using ontology to model content or user profile in their work along side with machine learning techniques, whereas [26], [24], [25] used knowledge designed graphs to represent the user model, or Q-learning [29] with machine learning techniques.

On the other hand, Azzi et al. [27] are more focused on users learning style. They proposes an approach that predicts the user learning style and stores then the collected data. We notice that most of the adaptation techniques used belong to two main ranges, to ontology for modeling and representation, and to machine learning methods. Also other researches tend to combine two at least methods in order to develop an hybrid technique.

These systems mainly evaluate the user performance and make recommendation based on collective preferences like Agbonifo and Akinsete [23] in their work experiments. This method is not the most efficient way due to the lack of specification in those rating (based on what and by who).

Content modeling of learning objects also is another part that should be considered as important as the profile modeling. Moreover it is worth noting the low number of pedagogical resources used in evaluation when seeking for users ratings about a course.

On the other hand the hybrid techniques implemented in those systems whom the semantic part for modeling content and profiles candidate them to be technically efficient as they are using latest technologies tendencies.

Table II gathers previously mentioned systems and lists the types of adaptation presented in the proposed work. We notice that only Boussakssou et al. [25] integrate an adaptation based on user action in their proposed work. Whereas [22], [24] described a group based adaptation and then a content adaptation in [24]. In [28] along with [24] propose an adaptation model that assures course adaptation. This adaptation relies on certain characteristics of the user such as background Knowledge and learning style using Q-learning in El Fazazi et al.s' works [28].

These comparison criteria are selected on the basis of the definition and the different types of adaptation mentioned above.

V. METHODOLOGY

Following our findings on the advantages and disadvantages of current adaptive recommendar systems, we propose a new architecture for piloting and customizing adaptive learning paths, while taking into account the users' profile, the training domain and the available educational resources, and adding synchronization in the collaborative mode between learners wishing to work in collaboration. This system is based on ontologies and a multi-agent system responsible of managing events that occur inside the system. Reasoning on ontologies allows to make tacit information explicit. Among other things, this allows for a better personalization of learning paths. On the other hand, multi-agent systems have shown their great capacity to orchestrate in real time a set of agents.

A. Adaptive and Collaborative Learning Piloting Architecture

This architecture is composed of a multi-agent system (MAS), which contains an agent manager representing the entry point of the main MAPE-K loop of the platform (cf. Fig. 2). This Agent analyzes the requests, processes them and manages the communication between the recommendation agents (RA), responsible for managing the creation of learning paths and the recommendation of educational resources.

TABLE II. COMPARISON IN TERM OF ADAPTATION

Reference	User Based	Machine Based
Sarwar et al. [22]	-	X
Agbonifo et al. [23]	-	-
Vagale et al. [24]	-	X
Boussaksou et al. [25]	X	-
Shi et al. [26]	-	-
Azzi et al. [27]	-	-
El Fazazi et al. [28]	-	X

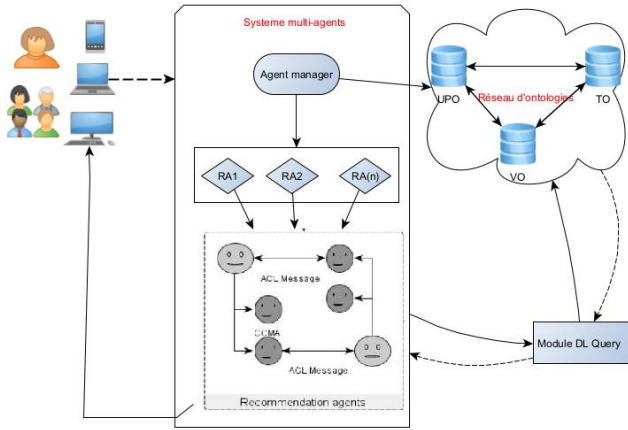


Fig. 2. SPACe-L Architecture.

B. Knowledge Base

The core of the platform is its knowledge representation by a network of ontologies describing three ontological models representing users profiles, training domains and video resources. This modularity is intended to facilitate the interoperability with other ontologies in the respect of the FAIR principles⁷. For example, the user representation (cf. Fig. 3) allows from the ontology FOAF data to be integrated. For the training domain, we can integrate ontologies describing competences like the ontology COMP2 proposed by G. Paquette [30].

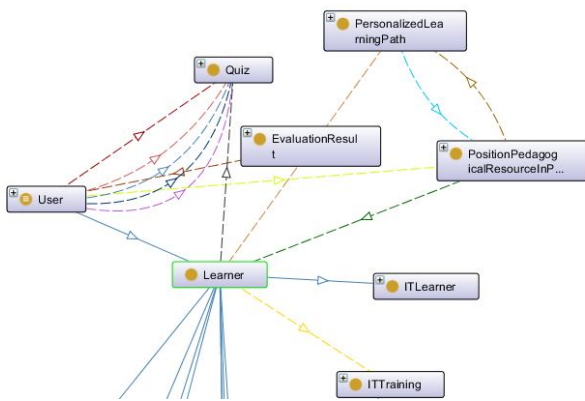


Fig. 3. Partial View of User Profile Ontology (UPO).

The partial view of UPO shown in Fig. 3 contains the personal information and preferences of the users. It mainly

describes learners, their specific information, their initial or acquired skills and the personalized learning paths already completed or ongoing.

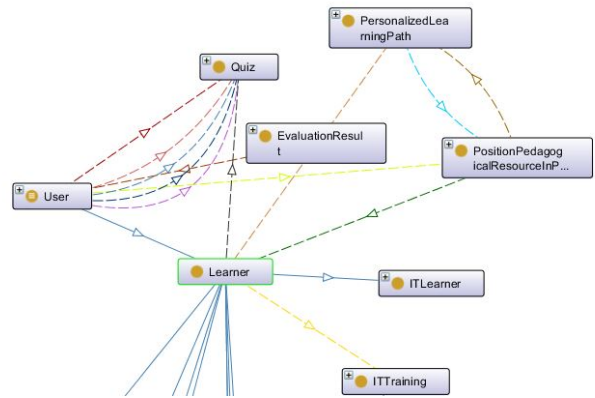


Fig. 4. Partial View of Training Ontology (TO).

The ontology of the training domains (TO) describes the competences to be acquired, the learning objects and the pedagogical resources that can be used in the different pedagogical units (Fig. 4).

C. Multi-Agent System

The multi-agent system (MAS) manages the events that occur in the system, under the supervision of the *Agent manager* who analyzes the requests received and manages the situation according to its nature. It plays a double role according to the learning situation, either individual through a recommendation agent, or collaborative. It then manages a network of recommendation agents for the synchronization of learners. The recommendation agent (RA) is associated to one user or group of users in collaborative situation. The recommendation agent will take care of the generation of the personalized path in the form of a graph by associating relevant pedagogical resources to each node of the graph.

The graph generation is done according to the user profile and the recommendation of the pedagogical resources according to several criteria including the learners' preferences, the duration of the session, but also the qualitative evaluations of the other learners, trainers or experts. The objective here is to maximize a fitness function (cf. Equation 1) which allows to dynamically generate a personalized learning path according to:

$$F = \sum_{i=1}^n W_i C_i \tag{1}$$

⁷<https://www.go-fair.org/fair-principles/>

Where W_i is the weight that defines the importance of C_i and n is the number of selected criteria of a pedagogical resource.

VI. DISCUSSION

Based on the observation from the study done in this paper, it is obvious that adaptation in a recommender systems is essential in order to provide the learner what suits her/him. Therefore, machine learning, ontological and hybrid techniques have been applied in different propositions. We mention in particular the machine learning collaborative filtering technique for its frequent use in those systems. It is reasonable to understand it is widely implicated in most of adaptive e-learning systems since it is a new form of the most traditional method of recommendation (recommendation based on personal user experience). In addition, collaborative filtering system features include recommending an item by classing a list of object based on whether it might be interesting to the user. They include also predicting for a specific item and its rating by a user [31].

It is required, however, to pay attention to some of the challenges that can and have arisen; such as users rating to a certain pedagogical object (courses, learning object, learning path, pedagogical resources, etc.). The integrity of that rating cannot be measured in reality, without exposing publicly the interest of the user or her/his personal information, that leads to another privacy problem. In addition to these problems, we include the unequal number of users and votes on object. George and Lal [7] have pointed out in their research works that the number of users is higher than the number of votes.

Content-based method relies on the interaction of the user and data collection after. Therefore item description is as much as important as the user behaviour, seeing that the recommendation is established based on that. The steps of content-based recommendation techniques are as follows: (i) at the start, item description is stored after analyse, to determine the preferences of a user regarding this item for future use; (ii) then a comparison mechanism is done between user profiles and attributes of these items to sort only related items with similarities with that profile. That said, it still represents multiple drawbacks. Let us mentioning user preferences and interest that change and that affect directly the recommendation. Another issue is the privacy previously mentioned of the user. In order for these methods to have accurate recommendation a large and precise amount of information must be extracted, and that might expose the user privacy policy. Synonymy is also another issue represented by the fact that some of items can have very close description but they still different, which lead to erroneous recommendation [32].

Thus, Semantic Web is a research field existing since the late 90s, especially ontologies, which is promising due to its ability of sharing, reusing and inferring knowledge including through Linked Open Data (LOD), and its level of interoperability. Moreover, it is a good candidate to the FAIR principles (Findable, Accessible, Interoperable, Reusable) [33], [34]. They have also managed to address most of these problems. There is no uniform model for the learner profile or structured material in e-learning, which makes ontology even more relevant [7]. In addition, e-learning requirement

can be satisfied by multiple uses of semantic web. This latter one is *Non-linear* as it allows user to describe the situation that she/he is currently in; for example the purpose of her/his learning, and the knowledge acquired. The Semantic Web is also *interactive* that agent can use commonly agreed service language, enabling collaboration between them. Despite the learning resources being distributed on the web, they are linked to one or more commonly accepted ontologies in the scope of semantic web (cf. LOD). Learning materials are distributed on the web, but they are linked to commonly agreed ontologie(s). This allows to build a course that is unique to the user by using semantic querying to find relevant subjects of interest [35]. Application of semantic web can create a responsive learning environment, a personalized learning materials where user only receives what suits her/him, and as much as decentralise content possible.

VII. CONCLUSIONS AND FUTURE WORKS

Adaptation in e-learning systems represents a trending research area. In this paper, we presented different adaptive e-learning systems representative of different categories. Several methods were experimented and compared, yet the existing methods have both benefits and drawbacks. The conflict of which one is more effective is still. Mainly the adaptation inside an e-learning environment is user centered even though many researches use the content-based method. Others tend to predict the learning style of the learner, or extract knowledge from user interaction and navigation history; while others lean to use techniques like collaborative filtering and machine learning methods. Except for the fact that user profile modeling remains the main axis to highly adapt content and the learner's need and interest. This being said modeling user is not an easy task to achieve, nor extraction her information by tracing her interactions through the web. Modeling user profile extends representing her interests, competences, expectations of the course and goals. It might reach her mental state at the learning session and after. We highlighted that modelling these new criteria implies a high complexity level in the adaptive process inside an e-learning system. That said the Semantic Web in a side is one sophisticated way to model a profile through the use of ontology. This research field can be highly explored and be employed to improve the current state of adaptive e-learning systems, especially the collaborative learning type which represents an important type of learning and increase learners motivation to reach new competences or reinforce competences.

However some of the relevant questions in that regard still exist such as how can the recommendation systems be improved? And in a more specific manner how is the adequate learning path recommended? How can one be sure we are actually getting the right pedagogical resources? All these questions concerns individual learning situations, it remains those regarding the collaborative situation mentioned earlier, how will the synchronisation between learner be established? Even if established how will the adaptation be maintained? How can we keep learners interested and motivated to finish the training and benefit it the most? How can we integrate citizen science in the scope of collaborative learning? These research questions are important to analyse and to focus on. In this paper we proposed a recommendation system based

on Semantic Web for knowledge representation and multi-agent system that manages the different events in the system. It seems to us that is a good way to answer of the above questions. However there are still several points to improve in order to obtain an advanced adaptive system. starting with enriching our ontology network with ontologies coming from some standards or norms of the educational sciences, and on other side improving response times for learning path and learning resource recommendations during users synchronization from what it concerns the multi-agent system performance.

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