International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 21 (2017) pp. 11476-11487


# A Proposed System for Learning Paths Personalization Using Learners Profiles

**Mohamed Bendahmane**
[1]*Designation Laboratory of Telecommunications Systems and the Decision Engineering, Faculty of Sciences,Ibn Tofail University Kenitra, Morocco.*

[1]*Orcid: 0000-0003-2710-2624*

**Brahim Elfalaki**
*Computer Science Department, Mohammadia Engineering School, Mohammed Vth University Rabat, Morocco.*

**Mohammed Benattou**
*Designation Laboratory of Telecommunications Systems and the Decision Engineering, Faculty of Sciences, Ibn Tofail University Kenitra, Morocco.*

**Abstract**

In education, the ultimate goal of every teacher is to transmit to the learners in a controlled and directed way, a know-how to acquire a competence in correct conditions. The heterogeneity of learners is a handicap to this learning process. Therefore, an optimal pedagogical path for one is not necessarily the same for the other. Thus, providing an interactive environment tailored to the learner's needs is one of the most important goals of e-learning environments.

In our proposal, it is a question of offering each learner a personalized course for the acquisition of the targeted competency. Our approach is based on the collaborative filtering concepts and adopting a system based on services focused on the learner's profile and his preferences.

In this paper, it would be prominent to individualize the learning path by proposing an adaptive test which offers a selection of optimal items in a sequence taking into account learner profile and learner progress. The evaluation of the performance of the proposed approach was tested. The results of the test show the accuracy of the proposed method.

**Keywords:** Personalized Learning, Learning Path, Learning Style Collaborative Filtering, Services-Oriented Architecture

## INTRODUCTION

Learning is defined as a process where knowledge is created through transformation of experience [1],[2]. The most common perceptions about learning include that it is a quantitative increase in knowledge or acquiring information of 'knowing a lot', memorizing or storing information that can be reproduced, acquiring facts that can be reproduced; acquiring; interpreting and understanding reality in a different way [3], [4].

E-Learning is a type of distance learning, and is characterized by "the use of new Internet 's technologies multimedia to improve learning quality by facilitating on the first hand the access to resources and services, and on the other hand exchanges and collaboration at a distance "[5]. This training mode has been the subject of several research studies to define standards, develop specifications, standardize and implement tools and platforms. Admittedly, Web technologies' use in education field offers new opportunities to implement new didactic intentions in new learning contexts. However, the quality of these pedagogical approaches in computing environments depends on their ability to provide learners with pedagogical paths adapted to their needs. In fact, learning process is a variable that depends on the prior knowledge, motivation and needs of individual learners, [6]. This understanding poses a problem that emphasizes the importance of developing an adaptive system, which considers the individual needs of learners towards an effective learning process and acquisition of knowledge.

The notion of adaptation is defined as the concept of making adjustments in the educational environment to accommodate diversity in the learner needs and abilities, in order to maintain the appropriate context for interaction. Adaptive sequencing is defined as the process for selecting of learning objects (LO) from a digital repository and sequencing them in an appropriate way which is appropriate for the targeted learning community or individuals [7].

In this perspective, many works have been done in this last decade about personalization and adaptation of learning using E-learning system [9], [10], [11]. In fact, several adaptive system were introduced, most are based on learner preferences [9], [10], [12].

The main of our work is to propose a personalized e-learning system based on collaborative filtering methods according to the cognitive style and learners learning preferences. Our proposal consists to adapt learning path to a learner's preferences by implementing an orchestrated web component in a service-oriented architecture. These components are responsible for extracting and collecting learners' traces, and adapting and regulating learning paths to learners preferences.

This paper is structured as follows: Section 2 gives the related work cited in literature. In Section 3 we present the design of our proposed system. In Section 4, results and evaluation of our research are presented, and the conclusion is given in the last section.

## RELATED WORK

The personalized e-learning systems allows to automatically adapting the content or the organization of courses to fit the learners needs. In the literature, there are many proposals that address the problem of adapting learning systems [13] [14] [15] [16] [17] [18]. These proposals come from very different research trends. However, they agreed on the main elements of an adaptive education system that can be summarized in:

- The learner model
- The pedagogical resource model
- The learning model
- The adaptation model

After a comparative study of different learning systems in Table1, we find that:

- The so-called "intelligent" systems are focusing on learning methods despite of the learner model.
- The hypermedia systems are based on resources model and learners' profiles without taking account of the learning processes

**Table 1:** Comparative Study of Adaptative Learning Systems[19]

| SYSTEMS / COMPONENTS | | AHA | ALFANET | ANATOM TUTOR | ELM ART | Inspire | Metadyne |
|---|---|---|---|---|---|---|---|
| Learner Model | Contents | Profile, level of knowledge | Level of knowledge | Profile | Prerequisite, level of knowledge | Profile, level of knowledge | Objectives, level of knowledge, profile |
| | technology | Concepts based | IMS-LIP | | | | |
| | Refresh | dynamically by the system | static | dynamically by the system | static | dynamic | dynamic |
| Resources Model | | Domain model | IMS-QTI, IEEE-LOM | Domain model | Domain model | metadata | Domain model |
| Learning Model | | Oriented content using fragments | Oriented activities | Oriented activities | Oriented activities | Oriented activities | Resources oriented |
| Adaptation | Type | Presentation and navigation | Contents, Presentation | Navigation, presentation | navigation | navigation | Navigation, presentation |
| | Technical aspect | Link annotation, link hiding using user model values | Feedback to author + learning paths for user profiles | Predefined sequence and stereotype knowledge | Rules of methods' selection | Rules of methods' selection | Rules of learning unit selection |
| | scope | contents | Learning paths | Test activities | contents | Learning paths | contents |

## BACKGROUND

Personalization and adaptation in learning environments are two very important requirements for providing an effective educational service on the Internet. Personalization and adaptation in educational systems are often associated with the Course sequences planning, that is producing an individualized learning path of learning objects for each learner, dynamically selecting the most appropriate ones at any moment [20]. We can classify Course sequences planning techniques into two categories:

- planning the entire learning path at the beginning with an eventual modification if necessary [20][21][22][23]).
- planning obtained in an implicit way, step-by-step, through adaptive navigation support techniques like [24] [25] [26].

These two techniques are based on the learners knowledge and the domain of interest.

In this work we address the problem of helping learner during his learning activity by means of an association between his cognitive state, his learning styles and the teacher's learning strategy.

## LEARNING STYLES

A learning style is defined as a characteristic of cognitive, affective, and psychological behavior that serves as a relatively stable indicator of how a learner perceives, interacts with, and responds to the learning environment [27]. Most known learning style models are Myers-Briggs model, Kolb model [28, 29, 30], Honey-Mumford model [29], Felder-Silverman model 29, 31,32], Grasha-Riechman model. The list of dimensions within mentioned learning style models is given in Table 2.

**Table 2:** Some known Learning styles models.

| Learning style model | Dimensions within the model |
|---|---|
| Kolb model | Converger/Diverger Assimilator/Accommodator |
| Honey-Mumford model | Activist/Reflector Theorist/Pragmatist |
| Felder-Silverman model | Sensory/Intuitive Visual/Verbal Inductive/Deductive Active/Reflective Sequential/Global |
| Grasha-Riechman model | Competitive/Collaborative Avoidant/Participant Dependent/Independent |
| Myers-Briggs model | Extravert/Introvert Intuitive/Sensing Feeling/Thinking Judging/Perceiving |

Our analysis of learning style models shows that the most widely used model nowadays is Felder-Silverman learning style model (FSLSM) [31].

In this work, we adopted the FSLSM's model [33], for three major reasons. Firstly, for its simplicity it is easy to implement. Secondly, it is the most widely used in the design of adaptive systems. Thirdly, FSLSM is based on tendencies, saying that learners with a high preference for certain behavior can also act sometimes differently [34]. The learner's preferences in the FSLSM, relating to education and learning, were collected from the literature [35, 36], as presented in the following:

- Active(A) :
  - Discuses, explain or test learned material.
  - In discussion forum, post more often in other to ask, discuss, and explain something
  - Perform more self assessment tests and more exercises as well as spend overall more time on exercise.
  - Spend very little time of studying examples since they prefer doing something by themselves rather than looking at how someone else has solved a problem.
- reflective(R) :
  - Thing about and work alone on learn material.
  - Participate passively in discussion forum and frequently reading the posting but only rarely posting by themselves.
  - They visit and spend more time on reading material like content objects as well as stay longer at outlines.
  - They tend to take longer on self-assessment tests as well as on the result page of self-assessments and exercises for reflecting on their results.
  - Expected to answer the same question in a self assessment test less often twice wrong
- Sensing (S) :
  - Prefer facts and data in learned materials - prefer examples, spend more time on examples
  - like to solve problems based on standard procedures, learn existing approaches and a high number of conducted self assessment tests and exercises in order to check the acquired knowledge.
  - Patient with details, work carefully but slowly
- Intuitive (I) :
  - like to study abstract theories and their underlying meaning
  - learn from content objects and use examples only as supplementary material. Spend higher time on content objects and lower time on examples.

  - creative and like challenges - answer questions about developing new solutions, which require the understanding of underlying theories and concepts.
- Visual (L) :
  - learn best from what they can see such as graphics images, and flow charts.
- Verbal (B) :
  - Prefer to learn from words, regardless whether they are spoken or written.
  - Tend to like communicating and discussing with others.
  - high number of visits and postings as well as high amount of time spent in a discussion forum can indicate a verbal learning style.
  - Expected to visit reading material such as content objects more often.
- Sequential (Q) :
  - more comfortable with details
  - Tend to go through the course step by step in a linear way.
- Global (G) :
  - like to see the “big picture” and connections to other fields.
  - the outline of the course and the chapters are of interest global learners.
  - a high number of visits and more time spent on such chapter outlines as well as on the course overview page indicate a global learning style.
  - they are interested in relating and connecting topics to each other, this help them to interpret predefined solutions and develop new solutions.
  - tend to learn in large leaps, sometimes skipping learning objects and jumping to more complex material.

In our approach we use the Index of Learning styles Questionnaire (ILSQ) proposed by Felder-Silverman model ,with 44 questions for assessing preferences [37]. For each question, the learner must choose one answer out of two alternatives a and b. The 44 questions fall into four sets of 11 questions each. Each set of questions defines one dimension of learner’s cognitive model, which is thus made up of four dimensions according to Felder (Table 3). The questions are provide four values, between +11 and -11, representing the learner’s learning style preferences of each dimension.

**Table 3:** Learning Style Dimensions.

| Dimension | Learning style | | ILS sets of Questions |
|---|---|---|---|
| processing | Active | Reflective | Q1,Q5,Q9,Q13,Q17,Q21,Q25,Q29,Q33,Q37,Q41 |
| perception | sensing | intuitive | Q2,Q6, Q10, Q14,Q18, Q22,Q26, Q30,Q34, Q38, Q42 |
| reception | Visual | Verbal | Q3,Q7, Q11, Q15,Q19, Q23,Q27, Q31,Q35, Q39, Q43 |
| understanding | Sequential | Global | Q4,Q8, Q12, Q16,Q20, Q24,Q28, Q32,Q36, Q40, Q44 |

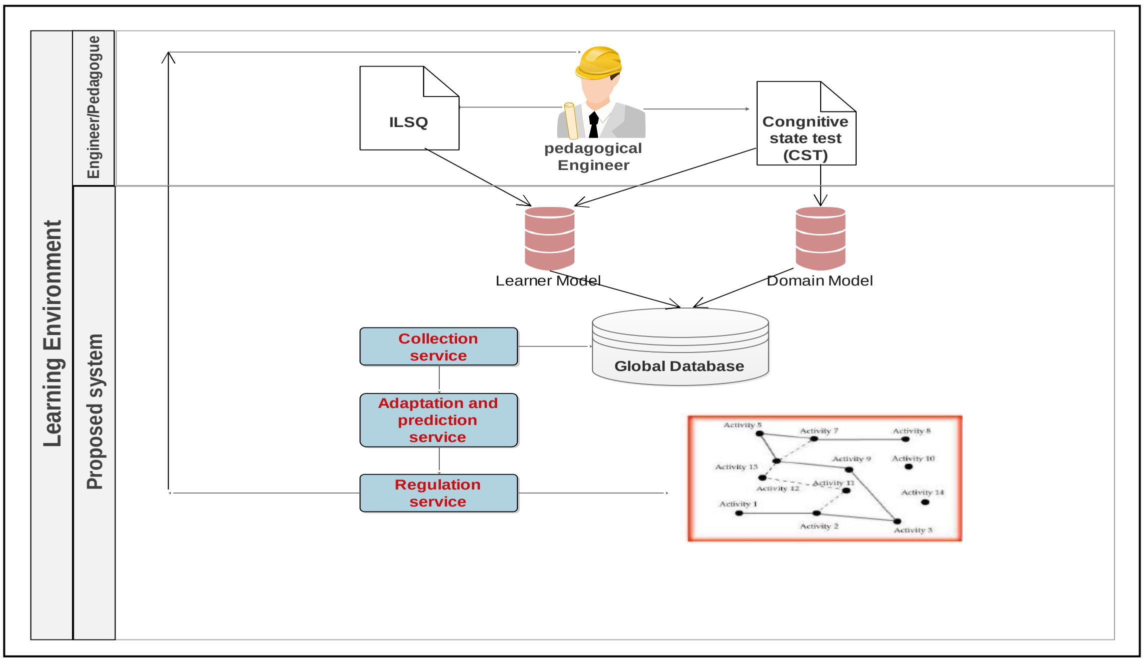


**Figure 1:** The proposed System Architecture

## PROPOSED SYSTEM

Our approach allows for choosing an effective learning path with regard to parameters such as learner learning style, and understanding degree, as well as the difficulty of course topics, and course learning materials.

For this, we opted for a model based on a service oriented architecture (SOA). The goal is to decompose the functionality of our web services model. We propose three orchestrated components in a SOA. These services are responsible for collection, analysis, adaptation, prediction and regulation of leaning objects (LO) to personalize learning path. Figure 1 shows the various stages of the proposed approach.

In our approach, The Teacher or the engineer pedagogue is responsible for the teacher's functionalities. He organize the course into chapters, each chapter is composed into learning objects (LO) , i.e., knowledge objects to acquire, each LO is associate with learning materiel (educational hypermedia). This information represent the domain model and is stored in the Global database.

The teacher is also responsible to define tests related to each LO for an eventual evaluation, and to create the initial Cognitive State Test (CST) for evaluating the starting knowledge of the learner, that is the knowledge already possessed by the learner with respect to the topic to be learned. the learner fills in both the CST and ILSQ developed by Felder and Silverman (FS), that extracts the learner's learning preferences according to the four dimensions of the FS Model. This information initialize the learner model LM and stored in the global database. The learner model contains in addition to these dynamic data that represent the learner's learning style (LS), other static information about learner such as name, age,.. etc.

The teacher specifies also her didactic strategies and defines for each topic her own instructional goal.

Figures 2,3 and 4 shows uses cases representing the functionalities of teacher , learner, and system administrator in our system.

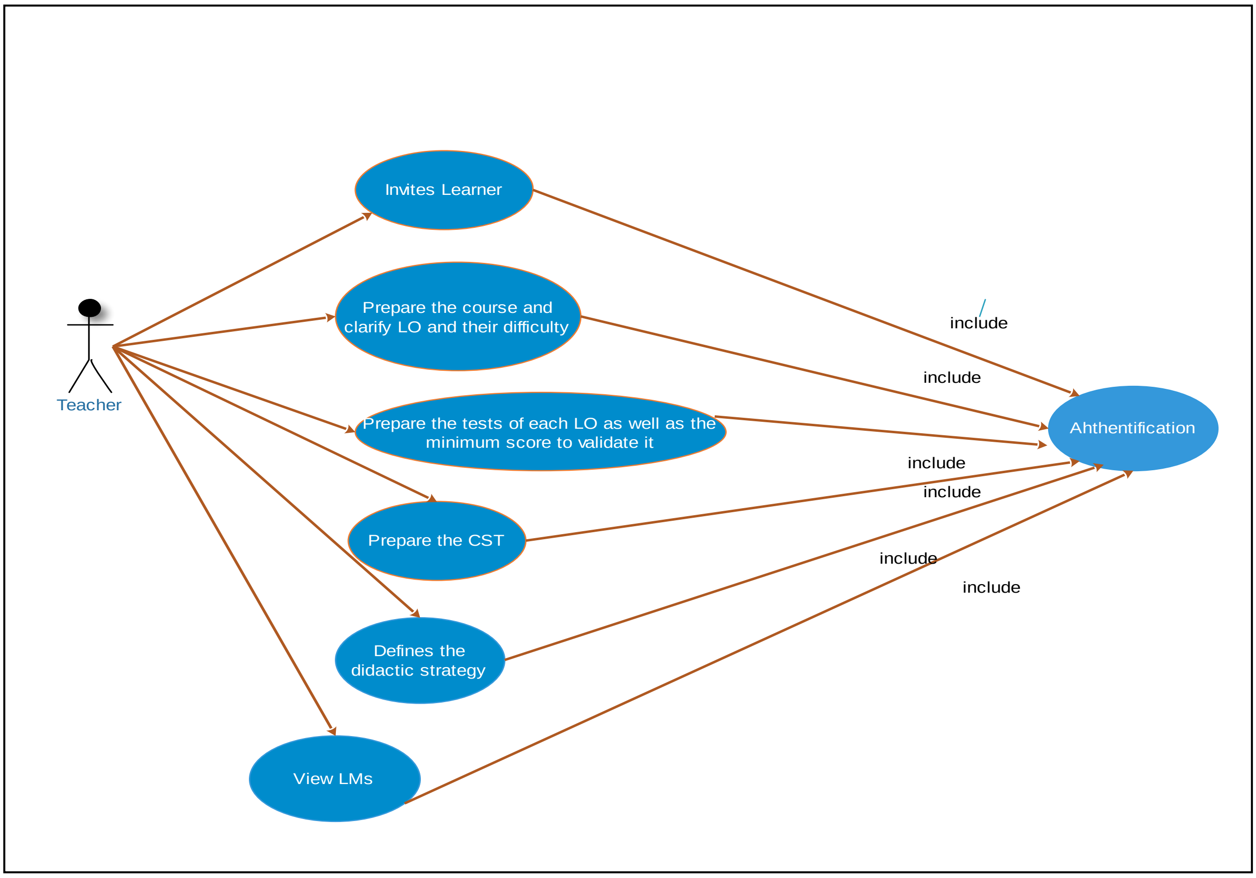


**Figure 2:** Teacher use cases

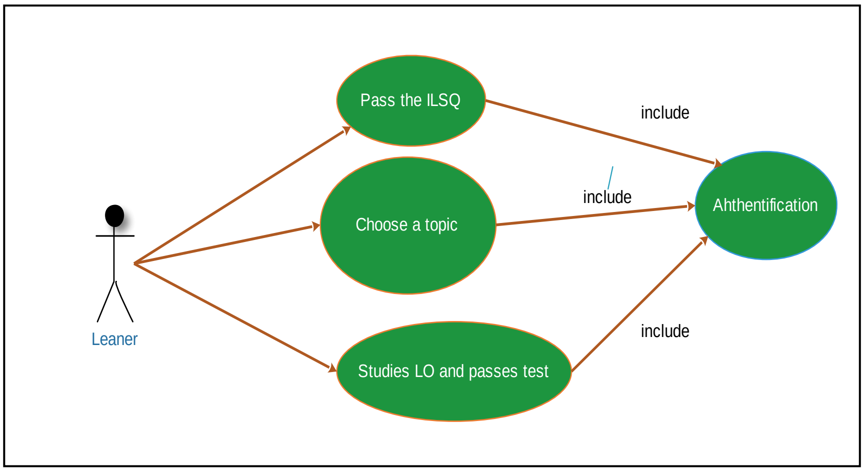


**Figure 3:** Leaner use cases

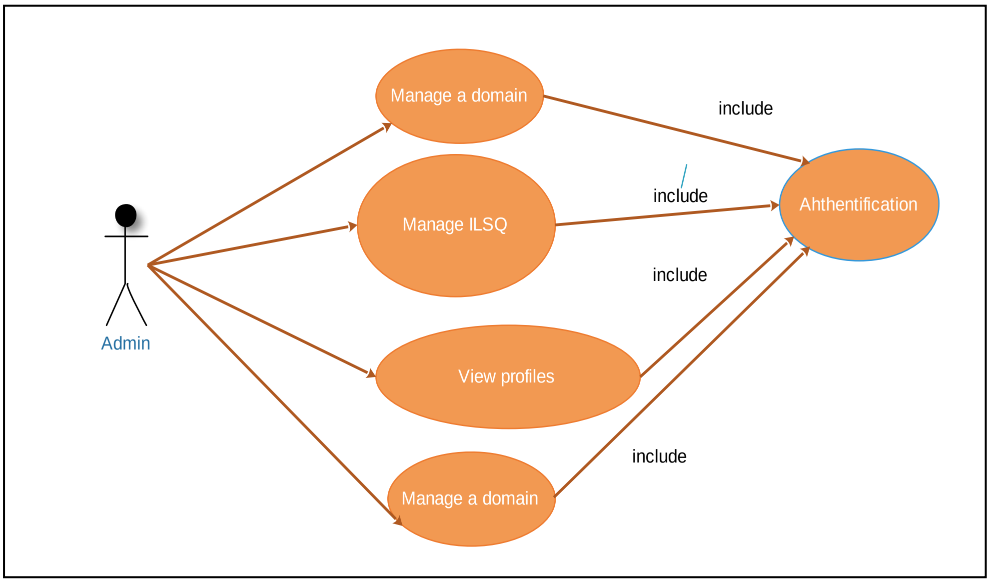


**Figure 4:** Administrator use cases

Before going into details about the components of the system, we introduce some definitions about the elements we are going to work with.

<u>*DEFINITION 1*</u>*: Learning Style LS* : A Learning Style according the ILSQ and which can be defined as followed:

$$LS= d_i \in[0,1]^8 = [i / 11]^8 \mid i=\{A_j,R_j,...G_j\} \qquad (1)$$

$d_i$ represents the priori probability of preference at $i^{th}$ ILSQ dimension and *A* represents Active, *R* Reflexive...etc. Using the ILSQ questionnaire, we may explicitly evaluate the $d_i$ value for each learner on numerical values in an interval [0, 1] such that 0 indicates a minimal satisfaction and 1 indicates a maximal satisfaction.

In this calculation done by (1), we divides by 11 the number of favorable answers to a LS, considering that the ILS has 11 questions for each FSLSM dimension, totaling 44 questions. In (1), i represents a LS(A,R,...G) in a FSLSM dimension, and j represents the number of favorable answers to a LS. An example would be if a learner answers 10 questions favorable to the Active LS we have: dA = 0,91. Therefore, we store 0.91 for the Active in the LM.

<u>*DEFINITION 2*</u>*: Difficulty level of a LO :*

$$DL_i= \{ -2, -1, 0, 1, 2\} \qquad (2)$$

$DL_i$ represents the difficulty level of the $i^{th}$ LO According to the LOM standard, the difficulty of a learning object is determined according to "how hard it is to work with or through this learning object for the typical intended target audience" [38]. To evaluate the difficulty level of a learning object, the Standard recommends 5 linguistic values: {*very easy(VE), easy(E), medium(M), difficult (D), very difficult(VD)}*.

*DEFINITION 3: Learner Knowledge Level*

$$KL_i = \{ -2, -1, 0, 1, 2\} \quad (3)$$

$KL_i$ shows the knowledge level of the $i^{th}$ learner. This parameter represents the knowledge level of a learner on the LO that he wants to learn. The results obtained with the preliminary test results CST We will use five levels of knowledge, namely {*very low (VL), low(L), medium(M), high(H), very high(VH)}*

Due to the fact that knowledge levels and difficulty levels are expressed in linguistic values, it is also needed to convert these values to the appropriate numeric values. For this purpose, the simple conversion table (Table 4) is used.

**Table 4:** Linguistic and numeric values for difficulty level of LO and knowledge level

| Linguistic | VE | E | M | D | VD |
|---|---|---|---|---|---|
| Numeric | -2 | -1 | 0 | 1 | 2 |

*DEFINITION 4: Threshold value*

A threshold value $\sigma_{LO}$ is a real number associated to LO defined as:

$$\sigma_{LO} = S_T / S_{max} \qquad 0 < \sigma_{LO} \leq 1 \quad (4)$$

being $S_T$ the lowest score of an assessment test of LO, as fixed by the teacher, in order to consider the LO acquired; $S_{max}$ is the highest possible score for that test

*DEFINITION 5 : Test*

A Test is a set of k questions with k ∈ N. To each question is associated a weight $Q_j \in R$. Each question has m answers, with m ∈ N and to each answer is associated a weight $p_i \in R$.

$S_{LO}$ is the score associated to a test; it assesses the learner knowledge of a LO

$$S_{LO} = \sum_{j=1}^{k} ( Q_j \cdot \sum_{i=1}^{m} p\, i) \quad (5)$$

where $p_i = 0$ for the answers the learner does not select.

*DEFINITION 6: Acquired LO (AL)*

It is a LO, with an associated success $S_{LO}$ :

$$S_{LO} > \sigma_{LO} \quad (6)$$

If such a test is not present in the LO the AL is considered acquired anyway.

Then we can define the Acquired LO mapping function that is a Boolean function that can be defined as follows:

$$AL = AMF(LO) = \begin{cases} 1 & \text{if } S_{LO} > \sigma_{LO} \\ 0 & \text{otherwise} \end{cases}$$

*DEFINITION 7: Required LO (RL)*

It is the set of required LO necessary for studying the current LO.

*DEFINITION 8: Cognitive State (CS)*

The Cognitive State CS is the set of all the LO possessed by the learner.

*DEFINITION 9: Learner Object (LO)*

A Learning Object LO is a 6-tuple:

$$LO = L\langle NR|AL|RL|DL|LS|T\rangle \quad (7)$$

where :

- NR is the numeric resource of the LO source.
- AL Acquired Level defined in definition 6.
- RL Required Level defined in definition 7
- LS is the learning style necessary for this LO.
- T is a pair of reels $T = (T_{min}; T_{max})$ which represents the estimated time interval for studying the LO, as prefixed by the teacher.

*DEFINITION 10: Learner Model (LM)*

The Learner Model LM is a pair:

$$LM = (CS; LS)$$

where :

- CS is the cognitive state
- LS is the learning style

### A. *Collection service*

This service is responsible to collect acquired data from the global database using SQL instructions. This data can concern essentially learner style, learner global data, learner knowledge level.

### B. *Adaptation and prediction service*

The adaptation and prediction service's role is to propose to the learner the most appropriate LO to his knowledge level and his LS, this happens using the collaborative filtering algorithm : k-nearest neighbor K-NN.

In the collaborative filtering algorithm, the system has a recorded set of LO and learners and how the learners rated those LO. Then algorithm is used to predict the rating for a learner who has not rated the LO yet. A rating for an item can be predicted from the ratings given to the LO by learners who are similar in taste to the given learner.

In the following we presenting the different steps of our system (Figure 5):

**Step 1 :** After being connected into the system, the learner passes the ILSQ and then the system updates his LM with the new LS. If learner has already passed the test then the collection service extracts his LS from the global database.

**Step 2 :** The Learner choose the target topic and then he passed the corresponding CST. the test results will allow the LM to be updated with learner's acquired LO

**Step 3** : The adaptation and prediction service use the K-NN algorithm, which is the most popular method used for classification, estimate, and prediction [39, 40]. This service classify learners and give predictions for learning objects. The idea is to find other learners whose past ratings for learning objects are similar for the active learner and use their ratings to predict current learner's preference for a learning object he/she has not rated.

The measurement for the weight for similarity between two learners *u, v* is the Pearson correlation coefficient [41, 42, 43].

$$w(u,v) = \frac{\sum_j^m (r_{u,j}-\bar{r}_u)(r_{v,j}-\bar{r}_v)}{\sqrt{\sum_j^m (r_{u,j}-\bar{r}_u)^2}\sqrt{\sum_j^m (r_{v,j}-\bar{r}_v)^2}}$$

where :

- $\bar{r}_u$ et $\bar{r}_v$ are the averages of learner u's and v's ratings respectively
- $r_{u,j}$ and $r_{v,j}$ are learner u's ratings and learner v's ratings for the learning object *j*.

If the learner *u* and *v* have a similar rating for a LO, $w(u,v) > 0$ . $|w(u,v)|$ indicates how much learner *u* tends to agree with learner *v* on the LO that both learners have already rated. If they have opposite ratings for a LO $w(u,v) < 0$. $|w(u;v)|$ Indicates how much they tend to disagree on the learning object that both again have already rated. Hence, if they don't correlate each other, $w(u,v)$ can be between -1 and 1.

And finally, compute the prediction for current learner u on learning object j. To generate predictions or for learner u, K-NN uses similarity to select a neighborhood N of neighbors of u. Once N has been selected, the recommender system combines the ratings of learners in N to generate prediction for learner u's preference for a learning object j:

$$P_{u,j} = \bar{r}_u + \frac{\sum_{v=1}^{n} w(u,v)(r_{v,j}-\bar{r}_v)}{\sum_{v=1}^{n} |w(u,v)|} \quad (8)$$

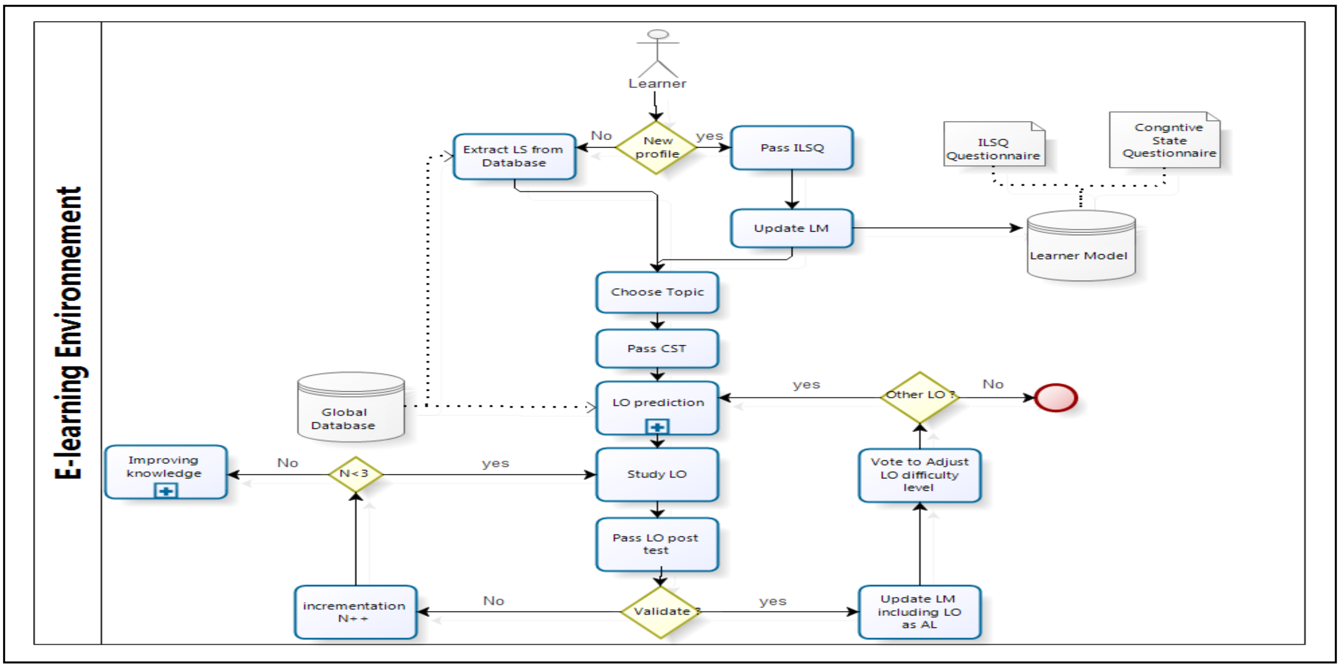


**Figure 5:** Business process diagram representing our system

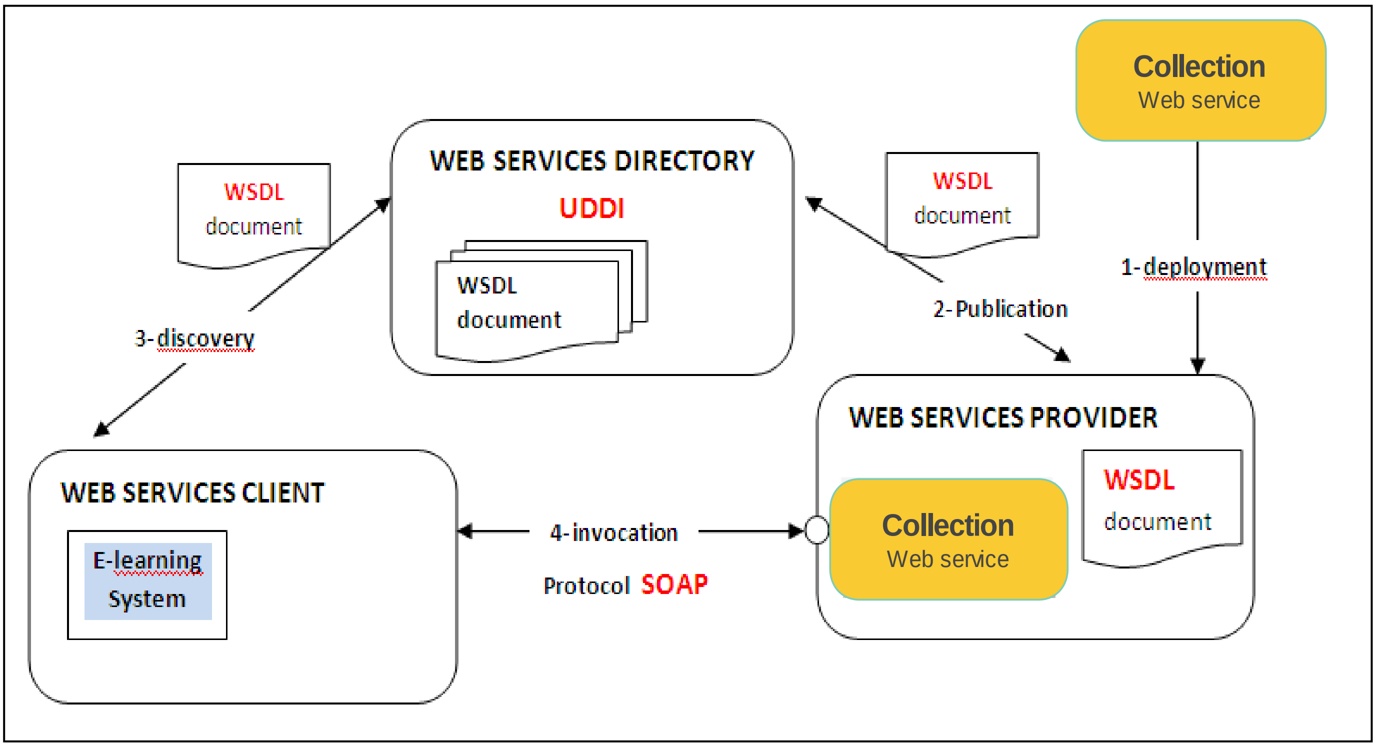


**Figure 6:** collection web service architecture

**Step 4** : the system choose the LO with the highest $P_{u,LO}$ value of equation (8) and propose it to the target learner with :

$$AL_{\text{(of this LO)}} \in LM_{\text{(of target learner)}}$$

After studying LO, the learner passes the LO's post-test and obtain a score. if he validates his LO then LO becomes an AL and will be added to the LM. If he does not validate his test ( $S_{LO} < \sigma_{LO}$ ) then the system will propose to learner to re-study the same LO at max 3 times.

### *C. regulation service*

Step 4 present the regulation service's role.

## IMPLEMENTATION CHOICES

Flexibility, reusability, interoperability and autonomy were the reasons why we choose Services-oriented architecture to implement our model. The idea is to use Web services to implement every system functionality.

Figure 6 explains "collection" web service operation principle.

The service requester will go through five steps :

- **Step 1** : At first it is necessary to describe web service functionality. This is done by Web Services Description Language (WSDL) within the service provider.
- **Step 2** : Once the service is defined and described, it will be published in a dedicated directory (UDDI Universal Description, Discovery and Integration) to make it accessible to customers.
- **Step 3** : The service requester must connect to UDDI directory to search for it.
- **Step 4** : Once it is found, customer must be saved from the provider associated with the service.
- **Step 5** : The service requester may then invoke it. This invocation and communication between services will be performed using Simple Object Access Protocol (SOAP). SOAP is a protocol described in XML and standardized by the W3C.

We present here (Figure 7) an extract from the prediction web service :

```
...
<s:schema elementFormDefault="passed">
<s:element name="sore_optimale">
<s:complexType>
<s:sequence>
<s:element minOccurs="0" maxOccurs="1" name="sc" type="s:string"/>
</s:sequence>
</s:complexType>
</s:element>
<s:element name="score_optimaleResponse">
<s:complexType>
<s:sequence>
<s:element minOccurs="0" maxOccurs="1" name=" score_optmaleResult"type="s:string"/>
</s:sequence>
</s:complexType>
</s:element>
</s:schema>
</wsdl:types>
<wsdl:message name=" score_optmaleSoapIn">
<wsdl:part name="parameters" element="tns: score_optmale"/>
</wsdl:message>
<wsdl:message name=" score_optmaleSoapOut">
<wsdl:part name="parameters" element="tns: score_optmaleResponse"/>
</wsdl:message>
<wsdl:portType name="Service4Soap">
<wsdl:operation name=" score_optmale">
<wsdl:input message="tns: score_optmaleSoapIn"/>
<wsdl:output message="tns: score_optmaleSoapOut"/>
…………..
```

**Figure 6:** An extract from the prediction web service

## CONCLUSION

Give the learner an adapted learning path to his needs is one of the most important objectives in e-learning. Several studies have focused on pedagogical personalization according to several angles. Our proposal is different, it is based on web services' independence and reusability to implement three components that are responsible for collection, prediction and regulation of leaning objects.

## REFRENCES

[1] Arthurs J., 2007, "A Juggling Act in the Classroom Teaching to E-learning: The Way for a Strong Definition", Teaching and Learning in Nursing, 2,.2-7.

[2] Kolb D.A., 1984, "Experimental Learning: Experience as the Source of Learning and Development", from https://www.amazon.com/Experiential-Learning-Experience-Source-Development/dp/0132952610

[3] Smith M.K.,1999, ”Learning Theory in Higher Education”, London, Routledge.

[4] Ramsden P.,1992, ”Learning to Teach in Higher Education”, London, Routledge.

[5] AWT ,2009,. "Qu'est-ce que l'e-Learning ? [What is e-Learning ?]", France : Agence Wallonne des Télécommunications. consulted 2017-04-01.

[6] Kareal F. & Klema J.,2006, "Adaptivity in e-learning". Current Developments in Technology-Assisted Education. pp. 260-264.

[7] Knolmayer G.F.,2003, “Decision Support Models for composing and navigating through e-learning objects”, Proc. the 36th IEEE Hawaii Inter. Conf. on System Sciences (HICSS’03)

[8] Mohan P., Greer J., McGalla G.,2003, “Instructional Planning with Learning Objects”, 11th International Conference on Artificial Intelligence in Education. pp. 51-58.

[9] Dorça A. F., Lima V. L., Fernandes A. M. and Lopes R. C., May 2013, “Comparing strategies for modeling students learning styles through reinforcement learning in adaptive and intelligent educational systems: An experimental analysis,”

Expert Systems with Applications, vol. 40, no. 6, pp. 2092-2101

[10] Klašnja-Milićević A., Vesin B., Ivanović M. and Budimac Z., April 2011, “E-Learning personalization based on hybrid recommendation strategy and learning style identification,” Computers & Education, vol. 56, no. 3, pp. 885-899.

[11] Kurilovas E., Kubilinskiene S., and Dagiene V., January 2014, “Web 3.0 – Based personalisation of learning objects in virtual learning environments,” Computers in Human Behavior, vol. 30, pp. 654-662

[12] Latham A., Crockett K., and McLean D., February 2014, “An adaptation algorithm for an intelligent natural language tutoring system,” Computers & Education, vol. 71, pp. 97-110.

[13] De Bra P. and Calvi L., 1998, "AHA! An open Adaptive Hypermedia Architecture", In The New Review of Hypermedia and Multimedia, 4, pages 115–139, Taylor Graham Publishers.

[14] Santos O. C., Boticario J. G and Barrera C. December 2004, "The Standards-based Architecture of the Adaptive Learning Environment aLFanet". In WSEAS Transactions on Computers, 3, pages 1814–1818.

[15] Beaumont I. , 1994, "User modeling in the interactive anatomy tutoring system ANATOM-TUTOR". In User Models and User Adapted Interaction, 4(1), pages 21–45

[16] Weber G. and Brusilovsky P., 2001, "ELM-ART: An Adaptive Versatile System for Web based Instruction", In International Journal of Artificial Intelligence in Education, 12, pages 351–384

[17] Grigoriadou M., Papanikalaou K., Kornilakis H., Magoulos G., 2001, “INSPIRE: An INtelligent System for Personalzed Instruction in a Remote Environment”; University of Athens.

[18] Delestre N., Pécuchet J.-P., Barry-Gréboval C., “Why to use a dynamic adaptive hypermedia for teaching, and how to design it?”

[19] Bendahmane M., El Falaki B., Benattou M., 2016, "Services-Oriented Model for the Regulation of Learning", in International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering Vol:10, No:7.

[20] Brusilowsky P. and Vassileva J., 2003, ”Course sequencing techniques for large-scale webbased education”, International Journal of Continuing Engineering Education and Life-long Learning, vol. 13, pp. 75-94

[21] Baldoni M., Baroglio C., Patti V., Torasso L., 2004, ”Reasoning about learning object metadata for adapting SCORM courseware”, Proc. of International Workshop on Engineering the Adaptive Web: Methods and Technologies for personalization and Adaptation (EAW’04),.

[22] Baldoni M., Baroglio C., Brunkhorst I., Marengo E.,. Patti V., 2007, ”Reasoning-Based Curriculum Sequencing and Validation: Integration in a Service-Oriented Architecture”, EC-TEL 2007, LNCS 4753, pp. 426-431.

[23] Sangineto E., Capuano N., Gaeta M., Micarelli A., 2008, ”Adaptive course generation through learning styles representation”, Universal Access in the Information Society (UAIS), vol. 7, no. 1-2, pp. 1-23.

[24] Brusilowsky P., 2001, ”Adaptive hypermedia”, User Modeling and User-Adapted Interaction, vol. 11, pp. 87-110.

[25] De Bra P., Smits D., and Stash N., 2006, ”Creating and delivering adaptive courses with AHA!”, Proc. EC-TEL ’06, pp. 21-33,.

[26] Weber G. and Brusilovsky P., 2001, ”Elm-art: An adaptive versatile system for web-based instruction”, International Journal of Artificial Intelligence in Education, vol. 12, pp. 351-384

[27] Felder R., Brent R., 2005, "Understanding Student Differences", Journal of Engineering Education., Vol 94(1), pp. 57-72.

[28] Liu Y., Ginther D. 1999, "Cognitive Styles and Distance Education", Online Journal of Distance Learning Administration., Vol 2(3), pp. 1-19.

[29] Sleigh J., 2002, "Learning Styles – from Theory to Practice. Training and Development in Australia", Australian Institute of Training and Development., 29(2), p. 44.

[30] Wikipedia. "Learning Styles", from: http://en.wikipedia.org/wiki/Learning_style (last visited on 23.06.2017).

[31] Graf S., Viola S., Kinshuk T. L., 2006, "Representative Characteristics of Felder-Silverman Learning Styles: an Empirical Model", Proceedings of the IADIS International Conference on Cognition and Exploratory Learning in Digital Age. pp. 235-242.

[32] Tinkham A. and Kamer C., 2003, "Learning Styles and Exploratory Testing", Proceedings of the Pacific Northwest Software Quality Conference.

[33] Felder R. and Soloman B., 1991, "Index of Learning Styles.", [Online]. Available:

http://www4.ncsu.edu/unity/lockers/users/f/felder/public/ILSpage.html. (last visited on 28.06.2017).

[34] Graf S., Kinshuk, Liu T.C., "Identifying Learning Styles in Learning Management Systems by Using Indications from Students' Behaviour".

[35] Pukkhem, N. and Vatanawood, V., 2011, "Personnalised learning object based on multi-agent model and learner's learning styles", Journal of Science and Teachnology, Vol : 5(3), 292-311.

[36] Franzoni, A.L. and Assar, S., 2009, "Student learning styles adaptation method based on teaching strategies and electronic media", Educational Technology & Society, Vol : 12(4), 15-29.

[37] Felder, R.; and Soloman, B., 2007, "Index of learning styles questionnaire", from https://www.webtools.ncsu.edu/learningstyles/

[38] Draft Standard for Learning Object Metadata, 2010, IEEE Learning Technology Standards Committee (LTSC). Retrieved from : http://ltsc.ieee.org/wg12/files/LOM_1484_12_1_v1_Final_Draft.pdf

[39] Daniel, T.L., 2005, "Discovering knowledge in data: An introduction to data mining", John Wiley & Sons

[40] Ekstrand, D.M.; Riedl, J.T.; and Konstan, J.A. 2011, "Collaborative filtering recommender systems", Foundations and Trends in Human-Computer Interaction, Vol : 4(2), pp : 81-173.

[41] Su, X.; and Khoshgoftaar, T.M., 2009, "A Survey of collaborative filtering techniques", Advances in Artificial Intelligence.

[42] Salehi, M. 2013, "Application of implicit and explicit attribute based collaborative filtering and BIDE for learning resource recommendation", Data & Knowledge Engineering, vol : 87, 130-145.

[43] Luo, X.; Xia, Y.; Qingsheng, Z.; and Li, Y. ,2013, "Boosting the K-nearestneighborhood based incremental collaborative filtering.", Knowledge-Based Systems, Vol : 53, 90-99.