Using Learning Styles and Neural Networks as an Approach to eLearning Content and Layout Adaptation

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Abstract. The eLearning's trend is changing; learning content has become the key issue of current eLearning. The eLearning in Portugal as in many other countries is not yet so widely used as an alternative to other forms of training: as is the case of traditional classroom. This is because learners don't identify their own learning style in the way the presentation of education content are done in the majority of eLearning material produced today, or not feel enough customization in the content to their own needs. This paper describes the design, development and implementation of the model of an adaptive course player that uses Kolb learning styles[1] and neural networks to model learners and dynamically generates navigation paths and layout adaptation. The system implements adaptation of individual recommendations and content adaptation based on learning styles, previous learner knowledge, learner's progress and persistence of their own preferences. This is a ongoing work, and we are using our own experience producing eLearning content and an actual eLearning project to evolve the way difficult domain content can be presented to different individuals or stereotyped groups (similar conceptual understanding) with a disparity of objectives, different kind of professional roles, dissimilar previous knowledge and different context.

Keywords: Adaptive Hypermedia; eLearning; Adaptive Educational Systems, navigation support, user modeling, intelligent tutoring systems, student models.

1 Introduction

eLearning has emerged as a prime topic in Portuguese educational strategy more than a decade ago, but it hasn't yet gained sufficient stakeholders and satisfactory results to be accepted without restrictions in all kind of educational contexts: long life learning, universities, schools, companies and other kind of organizations. Learning content has become the key issue of current e-Learning.

The first adoption phase of eLearning in Portugal was focused on platform's technology. The most important universities, yearly technology adopters in companies, business associations and research labs invest in testing, experimented and developed platforms for eLearning. Unfortunately, much time, money and enthusiasm were lost in these programs forgetting the most important: quality eLearning content in Portuguese language and well trained professionals in the area.

Modern developments in the field of content standardization for learning objects and metadata (LOM, SCORM)[2, 3] open new possibilities for adaptive educational media to work with masses of content and learning objects[4]. From our point of view, the appropriate modeling of the learner's needs and preferences, representation of pedagogical strategies, learning designs and assets as well as the runtime reconciliation of these elements, are the key issue for next generation eLearning. This can be done with the help of some kind of learning styles classification and a mechanism to produce personalized content.

In our own experience producing and implementing eLearning content, the previous knowledge of the subject matter, predominant learning style, and progress results combined with user control for a particular content presentation style are the main adaptive attributes to model a successful eLearning 2.0 content. In our work, we design and implement a learner model based on Kolb learning style inventory classification[1] and a dynamically generated presentation, Personalized Learning Paths, based on learning styles, previous knowledge of the subject, progress results and persistence of learner educational elements preferences. Some other work was done in this field using similar strategies: this is the case of ALE system developed at Fraunhofer Institute for Applied Information Technology[4] based on Felder-Silverman learning style classification, INSPIRE[4] an AEH-System that uses a learning style model based on Honey and Mumford[5], TANGOW[6, 7] based on learning styles by Felder and Soloman[8] which represents the profile in the model. Our model innovates in a way that we use not only a different learning style model based on Kolb inventory styles[9] but also four axis of adaptive attributes used on fly by a learning neuronal network engine that promotes recommendations on presentation layout and permits that all the time the learner has optional control in the GUI to allow users to adapt the content presentation. Based on individuals' previous experiences, the system adapts the weights in the learner model and suggests the new recommendations based on the new model parameters.

2 Personalized and Dynamic Content Presentation and Navigation

Learners' pedagogical and contextual parameters are inputs to the reconciliation engine that creates the personalized content in the sense of picking the right learning designs and activities [10]. Adaptivity in learning experience is accomplished by choosing the learning paths that suit the knowledge level and the acquired competencies of the learner. The core concept of our design is the Adaptive Hypermedia (AH) System, this is build as a model of the individual user and apply it for adaptation to that same user[11].

In our design, we use two types of adaptability:

1. Adaptive Presentation

2. Adaptive Navigation

For the first type we use three methods of adaptivity: Kolb Learning Styles, individual and global performance and user's preferences. For the second type we use a subject matter pre-test mapped to each learning object in the repository.
The most important adaptive methods are the learning styles and we design a learner model, which is determined with the Kolb (1984) learning styles inventory[1].

2.1 Kolb Learning Styles[1]

Kolb set out four preferences for learning:

- Feeling ("Concrete Experience" – CE)
- Watching ("Reflective Observation" – RO)
- Thinking ("Abstract Conceptualization – AC")
- Doing ("Active Experimentation – AE")

The combination of these styles gives us four learning styles or types:

- Reflector (Watching and Doing, Concrete-Reflective)
- Theorist (Watching and Thinking, Abstract-Reflective)
- Pragmatist (Thinking and Doing, Abstract-Active)
- Activist (Doing and Feeling, Concrete-Active)

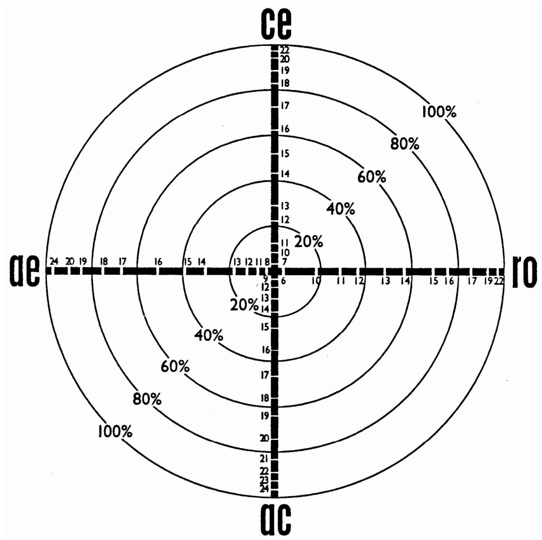


Fig. 1. Kolb's Learning Style Inventory Graph. Reflexive-Active and Concrete-Abstract dimensions[1].

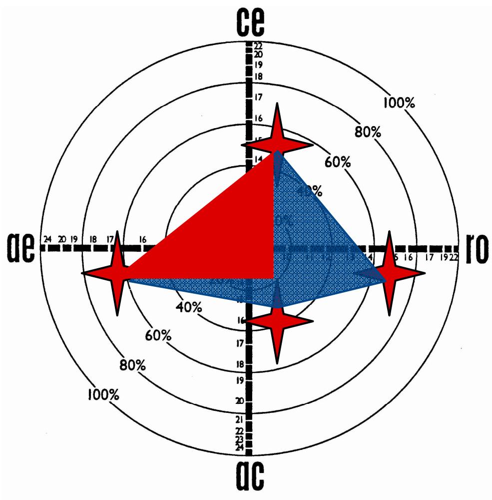
The Kolb inventory uses 9 sets (columns) of 4 words (rows) to locate the learner on 2D space. The learner must arrange each row of 4 words assigning a 1, 2, 3 or 4 value to the words that better suit their learning feeling. In the end we must transport the values to corresponding semi-axis, using a pattern of words.

	CE		RO		AC		AE	
1	Argumentative	4	Cautious	1	Topic-related	2	Practical	3
2	Receptive	1	Relevant	3	Analytic	4	Impartial	2
3	Feeling	3	Observing	1	Thinker	4	Doer	2
4	Accepting	3	Risk taker	1	Judging	2	Conscious	4
5	Intuitive	2	Productive	3	Logical	4	Questioning	1
6	Abstract	1	Observant	3	Concrete	4	Active	2
7	Now-focused	4	Reflective	3	Future-focused	1	Pragmatic	2
8	Experience	2	Observation	3	Structuring	4	Experimental	1
9	Intensive	1	Reserved	3	Rational	4	Responsible	2

CE						RO						AC						AE					
2	3	4	5	7	8	1	3	6	7	8	9	2	3	4	5	8	9	1	3	6	7	8	9
1	3	3	2	4	2																		

2) Compute Sums: CE = 16 RO = _____ AC = _____ AE = _____

Fig. 2. Kolb's Learning Style Inventory words. The red numbers are an example.



RO: 13
AC: 14
AE: 17
CE: 17

Fig. 3. Example of Kolb's Learning Style Inventory graph[1]. The area means the predominant learning style.

In his research Kolb concludes that no learner has one single style, we can even say that the limit has as many styles as there are individuals. In our design we use the following designations for the kolb learning styles: Reflector, Pragmatist, Theorist and Activist[5]. (fig 4).

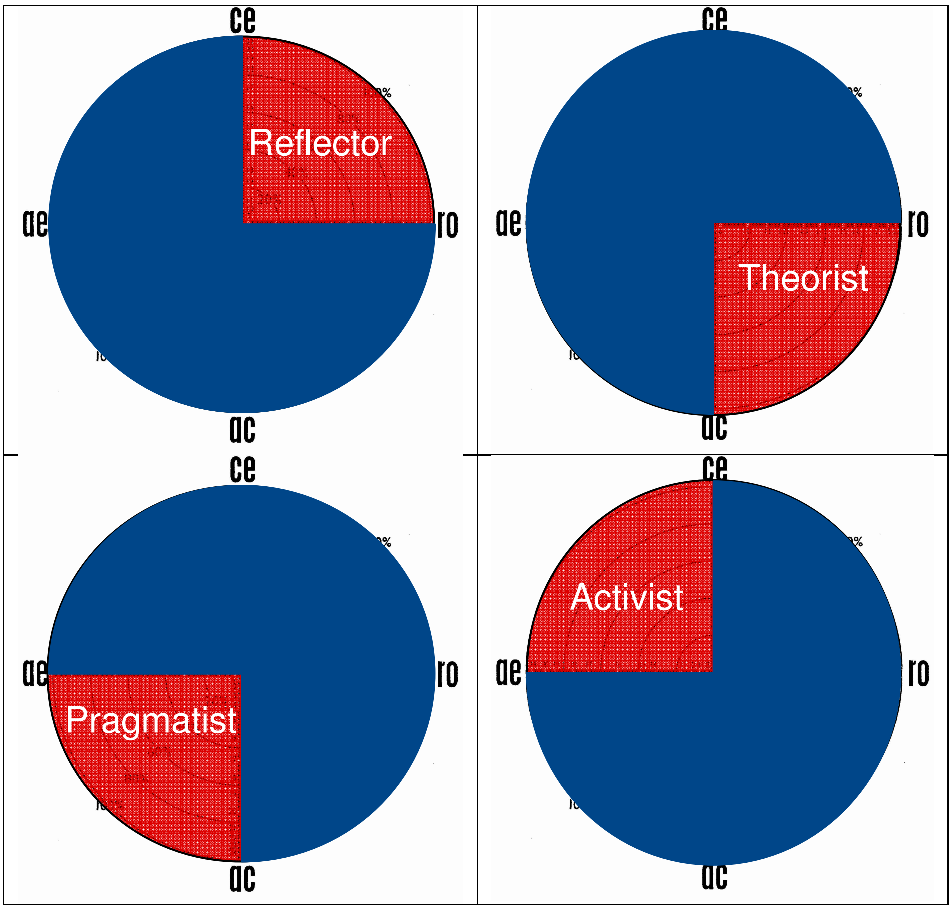


Fig. 4. Modified Kolb's Learning Styles[5].

Our design uses a Drag and Drop interface to process the self-administered questionnaire at the beginning of a new course. We present the results using a graph (figure 5) and we use color coding to distinguish the most predominant learning styles from the others. The results are then saved to a XML file as adaptive attributes.

```
<rede.neuronal>
  <proximo.aprendente>100</proximo.aprendente>
    <Aprendente Id="1">
      <Kolb.Inicial>
            <Data>07012008</Data>
            <Pragmatico>1</Pragmatico>

              <Teorico>0</teorico>
              <Reflexivo>0</Reflexivo>
              <Activo>0</Activo>
```

```
</Kolb.Inicial>
    …
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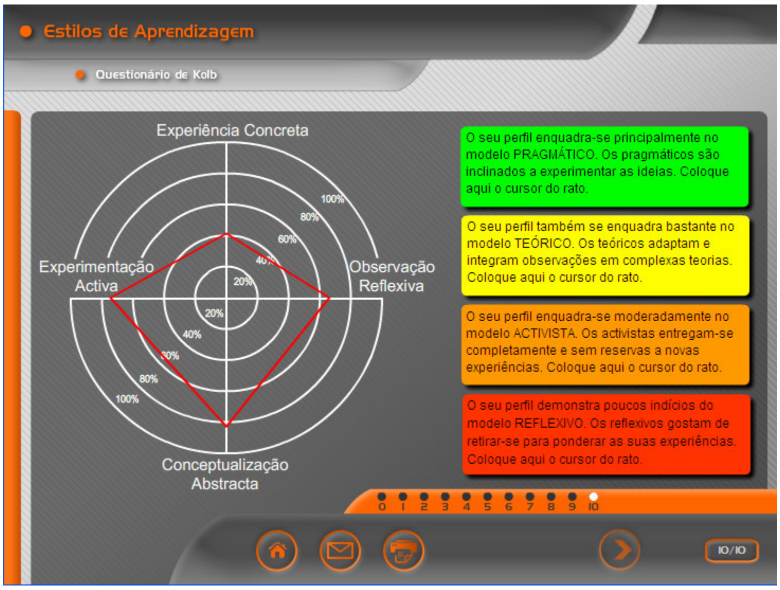

Fig. 5. Our implementation of Kolb's self-administered questionnaire[9].

2.2 Learning element Sequencing

Adaptivity in learning experience is accomplished by choosing the learning paths that suit the knowledge level and the acquired competencies of the learner[12]. In our design this is measured by the engine service based on the assessment results and on the learner's consumption performance of the Los (Learning Objects). Learning paths are portions of the concept domain ontologies. These ontologies represent essentially the curriculum constructs.

Fig. 6. Player learner Preferences Manual Graph Options.

Adaptability in learning experience is accomplished by choosing learning activities that suit the learner's pedagogical parameters and preferences. Being adaptable implies that the learners assume responsibility within the designated limits, and the also have freedom, yet guidance[12]. In our design we have a manual option graph (figure 5) that allows the learner to choose any of the available layouts for the content.

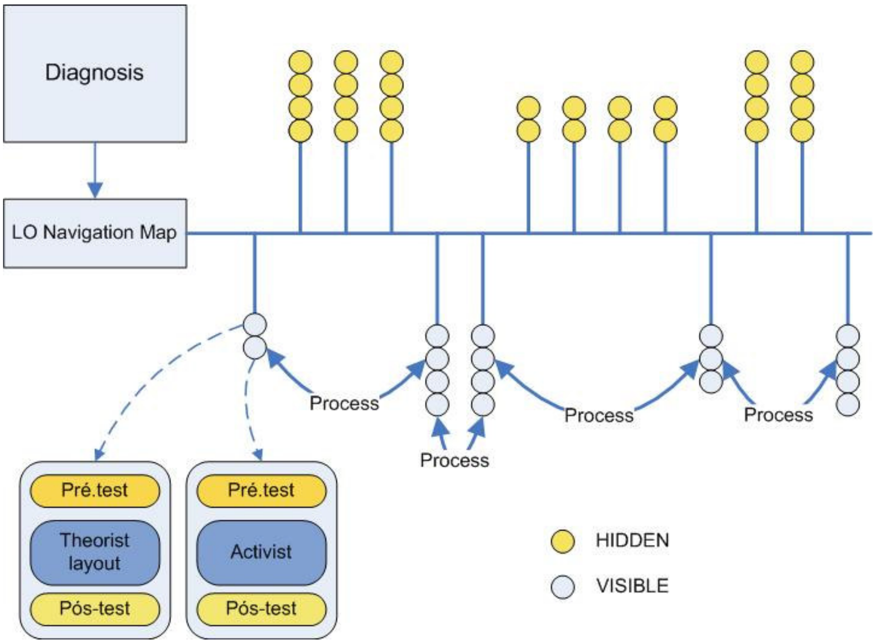

Fig. 7. CeLIP (Cesae eLearning Intelligent Player) Map Navigation Strategy.

Depending on the subject, their topic might have more or less presentation layout options. Learners with different learning styles react in different ways therefore they require different types of support when consuming the same learning object. This demarcation in support is provided not only for the search of an appropriate learning object, but also for the consumption of that learning object. Other important sequencing strategy is imposed by the kind of hidden options imposed by the initial diagnosis and ontological maps representing the curriculum.

2.3 Content/Presentation Adaptation

Targeting personalization, being adaptive and adaptable constrain the learning content to be developed and exploited by CeLIP (Cesae eLearning Intelligent Player). In our actual design each resource/page is developed, by authors and instructional designers, coding them in template pages manually. Each of these resources has metadata and can be reused in the development process of other courses. CeLIP can use contents like video, audio, text/graphics and interactivity simulations. CeLIP exploits the standardized technologies, such as SCORM 1.3 for learning objects.

The development of learning objects and learning designs should be coherent in order to prevent disharmony between these two. To overcome the Frankenstein effect [12] CeLIP employs only four types of final assembly layouts and the neuronal network engine tries to preserve the same style during the entire course using different weights for learning styles, performances as well as manual user preferences.

CeLIP determines the sequences of the learning objects at the very beginning, and an adaptive hidden strategy occults any LO that is considered not need to obtain the goals and objectives of the course. A primary aspect of content creation involves the curriculum analysis and accordingly the development of the ontological domain maps.

Another content creation's aspect is the development of knowledge representations for domains and learners. In order to match learner's knowledge to the knowledge designated for the domain, there should be a common representation model. However the representation for the learner will be let to evolve while the domain representation is bonded by the curriculum[12].

CeLIP uses four type of pedagogical layout strategies mapped to the four basic main styles defined by Kolb. We use sets of didactical elements composed in a way that the learner "feels at home".

3 CeLIP Player Architecture

CeLIP – Cesae eLearning Intelligent Player integrates new principles and tools in the field of Learning Design and Artificial Intelligence. This player uses a MLP (Multilayer Perceptron) neural network (figure 8) to predict the next presentation layout. This neural network is composed by layered arrangement of artificial neurons in which each neuron of a given layer feeds all the neurons of the next layer. This model forms a complex mapping from the input to the output. Our model is trained with the back propagation (BP) learning algorithm. This neuronal network is the core of our AI engine. Each time de engine process a new select, the state of each parameters is saved in a repository as a xml file. Our actual design only permits that the neural network operates on the behavior of one learner, don't permit global interaction between learners' models.

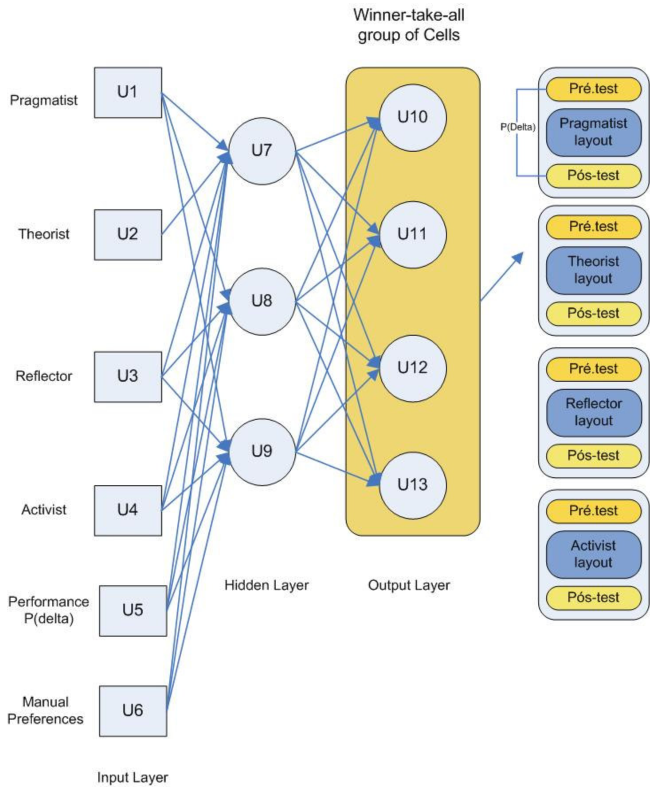

Fig. 8. CeLIP(Cesae eLearning Intelligent Player) Neurocontroller Architecture.

4 Example Workflow

Firstly, CeLIP (Cesae eLearning Intelligent Player) determines and employs a diagnosis in order to create a structure of LO's (Learning Objects) to cover the unit of study. The unit of study represents a portion of the curriculum domain map. This portion is evaluated respecting the knowledge level and the learner's acquired skills in order to decide which learning objects to be delivered.

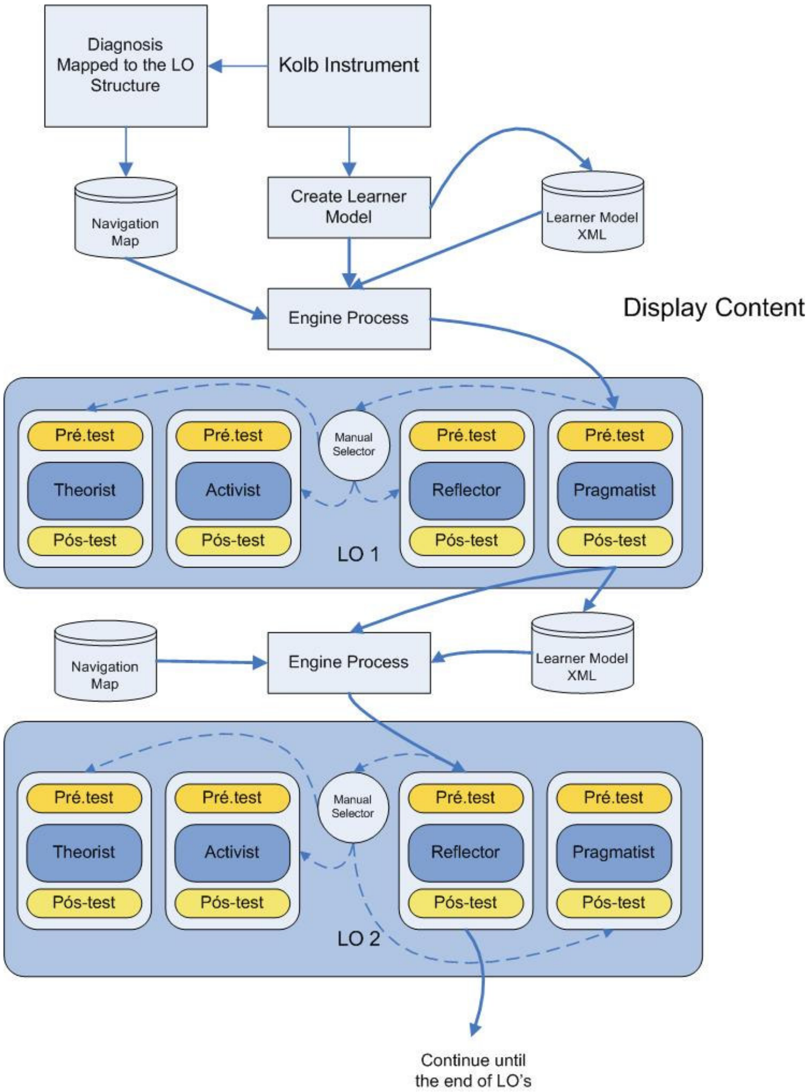

Fig. 9. CeLIP(Cesae eLearning Intelligent Player) Map Navigation Strategy.

The type of activities and presentation that harbor this chain of objects is determined by using the pedagogical and contextual parameters (learning styles, performance and user preferences).

For each step advance in the navigation structure, CeLIP searches and finds learning objects that best suit learning style of the learner, their preference and performance. Notice that, primarily the objects will have to suit the corresponding portion of the domain as well as a set of concepts and skills.

The workflow presented in (Figure 8) highlights the personalization process performed by CeLIP. The key stages in creating a personalized eLearning experience are modeling the learner, choosing an appropriate learning approach, selecting appropriate content with customized learning objects. The selection of LOs is dependent on the domain and the learner's existing knowledge on that domain.

5 Results and Future Work

We had implemented a first prototype of CeLIP (Cesae eLearning Intelligent Player) and we are now producing a course for central region of Portugal local authorities that become the first eLearning content using this technologies in Portuguese Language.

Fig. 10. Actual Instance of CeLIP -Cesae eLearning Intelligent Player.

We had found a lot of issues that we must investigate in future work: neuronal network learning parallelism; IMS LIP compatibility (by IMS Global Learning Consortium Inc.) ; Multi model approaches to model learner; time based learning (historical); short and long time learning duality. At end some authors expressed skepticism concerning the viability and validity of using learning style of the learner to adapt or personalize a learning environment to suit the needs of the learner[13].

6 Conclusions

In the present paper we have described the implementation of adaptive methods for content sequencing and adaptive presentation based on learning styles preferences, adaptive hiding result of a diagnosis test and a AI engine using a neuronal network that process the predictions of the best presentation layout for the next LO (learning Object) in the navigation sequence. This architecture is currently in the phase of implementation. We had implemented a user control in the GUI to allow learners to adapt the content presentation. In our first public presentation for "local authorities", we received good feedback from them.

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