DESIGN, IMPLEMENTATION AND EXPERIMENTAL EVALUATION OF A PEDAGOGY-DRIVEN FRAMEWORK TO SUPPORT PERSONALIZED LEARNING EXPERIENCES

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Abstract

Nowadays "one size fits all" solutions are not adequate to meet the needs of Learners. Effective personalization is necessary. The framework presented in this paper addresses this need by supporting dynamic construction of pedagogically-sound adaptive learning experiences using material in learning object repositories, taking into account the variety of learning needs of the Learners. Since pedagogy plays an important role to achieve this, a model for building abstract training scenarios (Learning Designs) has been also provided and an appropriate tool implemented, which guide the construction of pedagogically sound adaptive learning experiences and allow for the binding of appropriate learning resources at run-time according to the Learner Profiles. Experimental results show that the proposed framework can provide effective personalized learning experiences that reduce the learning time to achieve the desired learning outcomes thus increasing the learning efficiency compared with traditional "one size fits all" approaches.

Keywords

Distance Learning, Personalization, Instructional Design

1. INTRODUCTION

Different Learners have different learning styles, educational levels, previous knowledge, technical and other preferences and all these are needs and preferences that "one size fits all" solutions are not enough to satisfy them. Learners expect from systems that their personality and needs are known and taken into account in their learning activities. Moreover, the proliferation of the Internet and the wealth of content in Learning Object Repositories call for flexible solutions where content is not strictly bound with the learning plan but could be retrieved at run-time and ideally from many sources according to the Learner needs. Several research areas are related with the above challenges as Adaptive Hypermedia Systems, Intelligent Tutoring Systems, and Semantic Web (Brusilovsky, 1999). Although each area treats adaptivity of learning experiences from a different point of view, there is a convergence in the research community that pedagogy is important and should be represented in a consistent way. Moreover, the pedagogical model should be reusable and separated from content allowing appropriate learning resources according to the Learner profile to be bound to the training scenario at run-time.

In order to effectively support pedagogically-sound adaptive learning experiences, several issues need to be addressed:

1. Appropriate formulation and description of learning objects giving special attention to elements related with educational context (e.g. Learning Objectives).
2. Consistent representation of pedagogy separated from content according to a model that allows for the binding of appropriate learning objects to the learning scenarios at run-time.

3. Appropriate representation of Learner Profiles giving special attention to elements representing the learning needs of Learners (e.g. learning goals, previous knowledge, learning style, educational level).
4. Specification of a personalization component that taking into account all the above constructs adaptive learning experiences that fit to the Learner's needs and preferences.

In this paper, we present a framework that addresses the above issues. This framework allows for the dynamic creation of pedagogically-sound learning experiences taking into account the variety of the Learners and their individual needs. Among others this framework defines a model for the representation of abstract training scenarios (Learning Designs), where pedagogy is clearly separated from content. Appropriate Learning Designs are applied from the personalization processes performed by a personalization component to the construction of learning experiences where reusable learning objects are bound to the training scenario at run-time according to the Learner's individual needs and preferences (e.g. learning goals, previous knowledge, learning style, educational level etc.). This way, the Learning Designs can be exploited and reused by the personalization processes for the construction of learning experiences for different instructional contexts.

The structure of the rest of this paper is as follows: Section 2 presents the parameters that this framework considers as important input when performing personalization in eLearning. Section 3 presents the framework and a generic architecture for the dynamic pedagogy-driven creation of personalized learning experiences. Section 4 deals with the experimental evaluation of the proposed framework. A review of the related literature is presented in Section 5 and the paper ends with some concluding remarks (Section 6).

2. IMPORTANT PARAMETERS THAT AFFECT PERSONALIZATION IN ELEARNING

A learning experience can be considered as a learning plan with associated learning material (or in a broader view with services) that a Learner exploits in order to fulfill his/her learning goals. Ideally, both the construction of the learning plan and its association with appropriate learning material should be affected by the Learners' educational needs and preferences. But what are these educational needs and preferences that should be considered as input parameters in the personalization processes and what is their role in the construction of a learning plan and/or its binding with appropriate learning resources? We argue that the following parameters affect learning processes and we describe them in the following sections:

- The **Learning Style**: With simple words, the learning style (or learning preference) is the way a Learner tends to learn best. It involves the Learner's preferred method of taking in, organizing, and making sense of information. Education research and practice have demonstrated that learning can be enhanced when the instructional process accommodates the various learning styles of students (Buch & Bartley, 2002). Thus, learning and cognitive styles have generated a significant amount of interest because of the influence they can have on the effectiveness of delivery of teaching and pedagogical materials for a Learner (iClass Project, 2006; Goold and Rimmer, 2000; Griggs, 1991a; Lang et al., 1999; Montgomery and Grout, 1998; Renniger et al., 1992; Warren and Dziuban, 1997; Wilson, 1996).
- The **Educational Level** and **Difficulty**: It is important for a learning experience to be aligned with the educational level of the target Learner regarding a domain and his/her preferred difficulty in order to be able to participate in corresponding learning activities,

consume associated learning resources and transform them into knowledge. Educational level and difficulty should be taken into account both in the organization of a learning experience and its associated learning material. Thus, learning objects should also contain this info in their descriptions in order to be able to be selected in the personalization procedure.

- **Learner Goals/Objectives**: The Learner Goals/Objectives are an important parameter when performing personalization because they express what Learner considers as important to learn and more specifically what (s)he wants to be able to do after taking a learning experience. A learning experience that is built to satisfy Learner Goals can significantly reduce learning time while in parallel increase the efficiency of learning. A popular way for the formation of Learning Objectives is Bloom's Taxonomy of educational objectives (Bloom and Krathwohl, 1965). Bloom's taxonomy is comprised of six levels, namely: knowledge, comprehension, application, analysis, synthesis, and evaluation. Each level has a corresponding set of descriptive verbs that can be used to form Learning Objectives.
- **Previous Knowledge**: Taking into account the previous knowledge (background) of Learners can significantly reduce learning time by excluding from the learning experiences those activities that are related with learning objectives which have been fulfilled by the Learner at a satisfactory level. The information about previous knowledge can be extracted from the satisfaction level of the Learner's Goals. Moreover, the Learner should be able to decide and de-fine when his/her learning goals should be considered as satisfied (e.g. if the satisfaction of a Learner Goal is measured through a float number from 0 to 1 (s)he could say that Learner Goals with satisfaction level above 0.7 should be considered as satisfied). Of course, it is assumed that an appropriate Learning Management System is used that is able to continuously track Learners through their interaction with learning experiences and update this info.
- **Technical Preferences**: Technical preferences can include information about Learner's devices, internet connection etc. These preferences do not influence the organization of the learning plan but they are taken into account in the selection of appropriate learning objects.
- **Other Preferences**: Preferences regarding language, learning provider (the author or organization making available the learning objects), learning planner (the person that develops Learning Designs), etc. Preferences regarding language and learning provider affect the selection of learning objects, while the preference regarding learning planner affects the selection of the learning plan.

3. THE FRAMEWORK FOR THE DYNAMIC PEDAGOGY-DRIVEN CREATION OF PERSONALIZED LEARNING EXPERIENCES

In the architecture depicted in Figure 1 one can see that in the proposed personalization framework personalized learning experiences are created in appropriate form (e.g. as a SCORM package) using reusable learning objects residing at Learning Object Repositories in order to satisfy Learner needs and preferences expressed in Learner Profiles. To achieve this, the system consults Learning Designs (i.e. pedagogical templates) that describe how certain subjects should be taught.

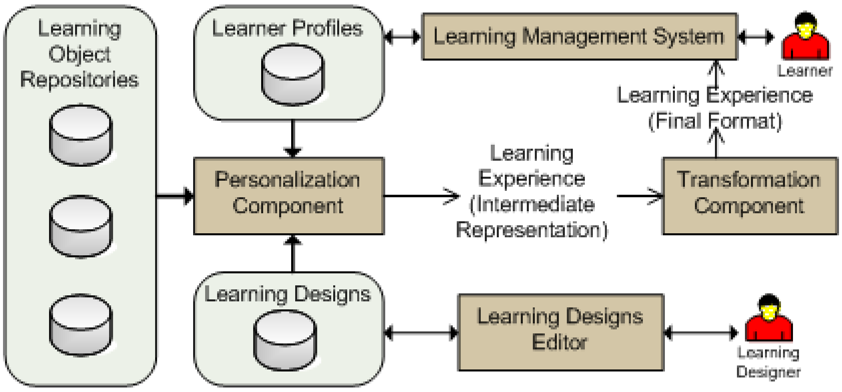

Figure 1. Overall architecture for the dynamic construction of pedagogy-sound personalized learning experiences

The main component of this architecture is the *Personalization Component*, which takes into account the *Learner Profile* and tries to find an appropriate *Learning Design* that will be thereafter applied to the construction of a learning experience. Then, based on the selected Learning Design, which is essentially a hierarchy of activities, the component is able to bind specific *Learning Objects* to each activity using information from the Learner's Profile and builds an *intermediate representation of the learning experience*. Finally, a *Transformation Component* creates an appropriate format of the *learning experience* (e.g. a SCORM package) from this intermediate representation. A special tool, called *Learning Designs Editor* has been also implemented for the creation of Learning Designs.

Finally, it is assumed that an appropriate *Learning Management System (LMS)* (e.g. a SCORM compliant LMS) is used to deliver the constructed personalized learning experience (i.e. in the form of a SCORM package) to the Learner. This LMS is also able to track Learner's behavior and progress in order to keep the Learner Profile up to date.

3.1 Learner Profiles

The parameters described earlier as important to personalization and their relations are normalized within the conceptual model illustrated in Figure 2 and could be considered as a part of a Learner Profile, since they describe in some extent a Learner. We will refer to the model of Figure 2 as the Learner Model noticing that a Learner Profile may contain more information; we just focus on what is or what is considered as important by us for the dynamic creation of personalized learning experiences.

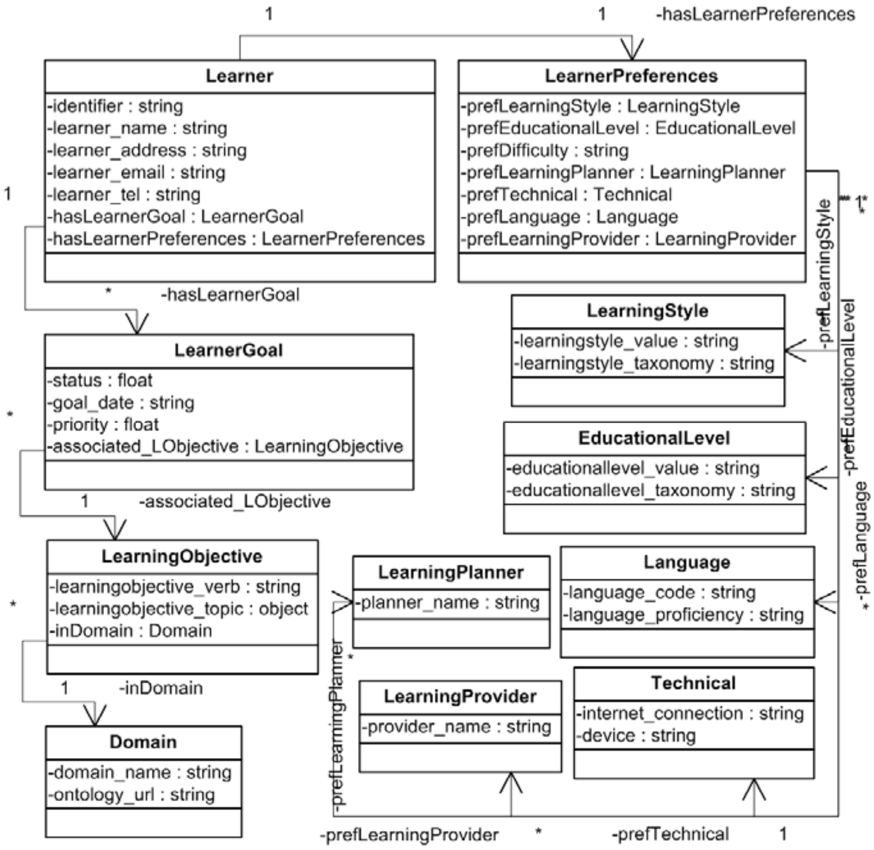

Figure 2. Learner Profile classes related with the dynamic creation of personalized learning experiences

A *LearnerGoal* is expressed in terms of *LearningObjectives*. Each *LearningObjective* is composed of: (a) a *learningobjective_verb*, taken from a subset of Bloom's Taxonomy (Bloom and Krathwohl, 1965) and (b) a *learningobjective_topic* that indicates the topic that the Learning Objective is about, referencing a concept or individual of a domain ontology. A Learner can have many *LearnerGoals*. A LearnerGoal has a *status* property (float in [0, 1]) indicating the satisfaction level of the goal (0 represents no satisfaction, 1 fully satisfied). Using this information one can also infer the previous knowledge of the Learner. The Learner can also define a *priority* for each LearnerGoal. The Learner can have several types of Preferences: *EducationalLevel* and *LearningStyle* matching with the corresponding elements of the instructional ontology, *Language*, *LearningProvider* (the author or organization making available the learning objects), *LearningPlanner* (the person that develops Learning Designs) and *Technical* preferences.

3.2 Learning Designs

In all major educational approaches learners perform activities in an environment with resources. In general, a learning design is a way of modeling learning activities and scenarios, as different types of learners prefer different learning approaches depending on their learning styles. Our approach regarding learning designs is fully aligned with the above definition. Specifically, in this framework, Learning Designs are abstract training scenarios that are constructed according to the instructional model presented in Figure 3.

In comparison with other approaches, this model has the important characteristic that learning objects are not bound to the training scenarios at design time, as in current eLearning standards and specifications (e.g. IMS Learning Design - IMS LD - and SCORM). Whereas, pedagogy is separated and independent from content achieving this way reusability of Learning Designs or parts of them that can be used from the systems for the construction of “real” personalized learning experiences, where appropriate learning objects according to the Learner Profile are bound to the learning experience at run-time taking into account several parameters of the Learner Profile. This is possible, since the model gives the opportunity to specify in each Activity the learning objects’ requirements, instead of binding the learning objects themselves. This ontology exploits some elements and ideas from IMS LD and LOM. These preferences do not influence the organization of the learning plan but they are taken into account in the selection of appropriate learning objects.

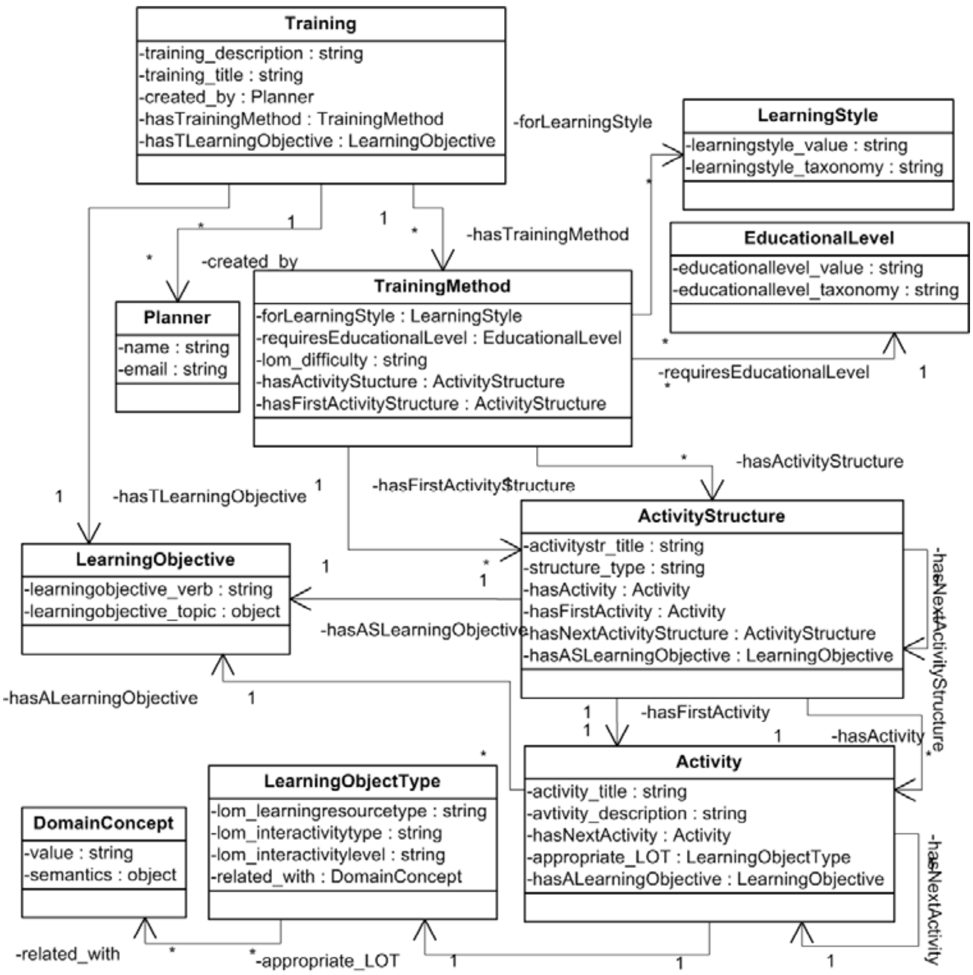

Figure 3. The instructional model used in the construction of Learning Designs

A *Training* (about a specific subject) is a collection of *TrainingMethods* that refer to the different ways the same subject can be taught depending on the *LearningStyle*, the *EducationalLevel* of the Learner and the preferred difficulty. There are several categorizations of Learning Styles and Educational Levels, thus these elements are flexible so that being able to point to values of different taxonomies. A *TrainingMethod* consists of a hierarchy of reusable *ActivityStructures* built from reusable Activities. Each *Training*, *ActivityStructure* and *Activity* is connected with a *LearningObjective*. Each *LearningObjective* is defined using the approach presented earlier. The *LearningObjectType* is used to describe the desired learning object characteristics without binding specific objects with Activities at design time. Via the *related_with* property we can further restrict the preferred learning objects according to their constituent parts (if they are semantically annotated) connecting them with *DomainConcepts* which refer to concepts or individuals from a domain ontology.

Initially this instructional model was implemented as an ontology coded in OWL and Learning Designs were developed as instances of this ontology. Later, a more flexible implementation based on XML was adopted. Here, we present an example of a simple Learning Design (part of it) for the teaching of SCORM eLearning Standard built according to the presented instructional model:

```
<learningDesign>
  <metaData>
    <!– LOM Metadata -->
  </metaData>
  <training id="T1" lobjectiveref="LVT1">
    <title>SCORM</title>
    <description>Training about SCORM </description>
    <trainingMethod id="TM1">
      <learningStyle>
        <source>http://…/learningstyles.owl </source>
        <value>GeneralToSpecific</value>
      </learningStyle>
      <educationalLevel>
        <source>http://…/educationallevels.owl</source>
        <value>Further</value>
      </educationalLevel>
      <difficulty>medium</difficulty>
      <activityStructure id="AS1" lobjectiveref="LVAS1" op="AND">
        <title>SCORM Overview</title>
        <activity id="A1" lobjectiveref="LVA1" lotref="LOTA1">
          <title>eLearning Standards Introduction</title>
        </activity>
        <activity id="A2" lobjectiveref="LVA2" lotref="LOTA2">
          <title>Advanced Distributed Learning (ADL)</title>
        </activity>
        <activity id="A3" lobjectiveref="LVA3" lotref="LOTA3">
          <title>What is SCORM?</title>
        </activity>
      </activityStructure>
      <activityStructure id="AS2" lobjectiveref="LVAS2" op="AND">
        <title>Content Aggregation Model</title>
        <activity id="A4" lobjectiveref="LVA4" lotref="LOTA4">
          <title>What is the Content Aggregation Model?</title>
        </activity>
        <activity id="A5" lobjectiveref="LVA5" lotref="LOTA5">
         <title>Content Model</title>
        </activity>
        <activityStructure id="AS3" lobjectiveref="LVAS3" op="AND">
          <title>Content Model Components</title>
          <activity id="A6" lobjectiveref="LVA6" lotref="LOTA6">
             <title>Assets</title>
          </activity>
             ...
        </activityStructure>
      </activityStructure>
    </trainingMethod>
    <trainingMethod id="TM2">
     <!—Another TM for other L.Style, Ed.Level and Difficulty -->
    </trainingMethod>
 </training>

<!—Learning Objectives associated with Training, Activities Structures or Activities. -->
<learningObjectives>
  <learningObjective id="LVT1">
   <verb>comprehend</verb>
   <topic>
<!- The Url of a domain ontology describing the SCORM domain -->
     <source>http://somehost/scorm2004ontology.owl
```

```
      </source>
      <value>SCORM</value>
    </topic>
   </learningObjective>
   <learningObjective id="LVAS1">
    <verb>describe</verb>
    <topic>
      <source>http://somehost/scorm2004ontology.owl
      </source>
     <value>SCORM</value>
    </topic>
   </learningObjective>
    ...
 </learningObjectives>

<!—Desired Learning Objects Characteristics to be connected with Activities at run-time-->
 <lots>
   <!-- lot for Activity "Assets" -->
   <lot id="LOTA6">
    <learningResourceType>slide</learningResourceType>
    <format>text/html</format>
    <interactivityType>active</interactivityType>
    <interactivityLevel>very low</interactivityLevel>
   </lot>
    ...
  </lots>
<learningDesign>
```

3.2.1 The Learning Designs Editor

The specification of Learning Designs is done using an editor that provides an intuitive GUI and is based on the above instructional model. The editor is able to create a Learning Design, open an existing one for further editing or reuse of a Learning Design or parts of it in the creation of other Learning Designs. Each Learning Design is presented in a hierarchical structure with its underlying Training Methods, Activity Structures and Activities in the form of a tree. Each tree node can be edited in a special form that contains all the corresponding properties. After editing a Learning Design the user can save it. At this point a set of well-formed rules are applied to check the structure of the Learning Design and find any inconsistencies that may be present and the user is informed about these inconsistencies so that he can handle them.

Figure 4 presents a screenshot of the Learning Designs Editor used to develop a Learning Design related to the teaching of Bulgarian Iconography. Four Training Methods are associated with this Learning Design forming alternative instructional paths for different combinations of learning style, educational level and difficulty. The screen shot also shows the editing form for a specific Activity inside the first Activity Structure of the first Training Method. The form contains fields for the editing of the title, the description, the Learning Object Type of the Activity.

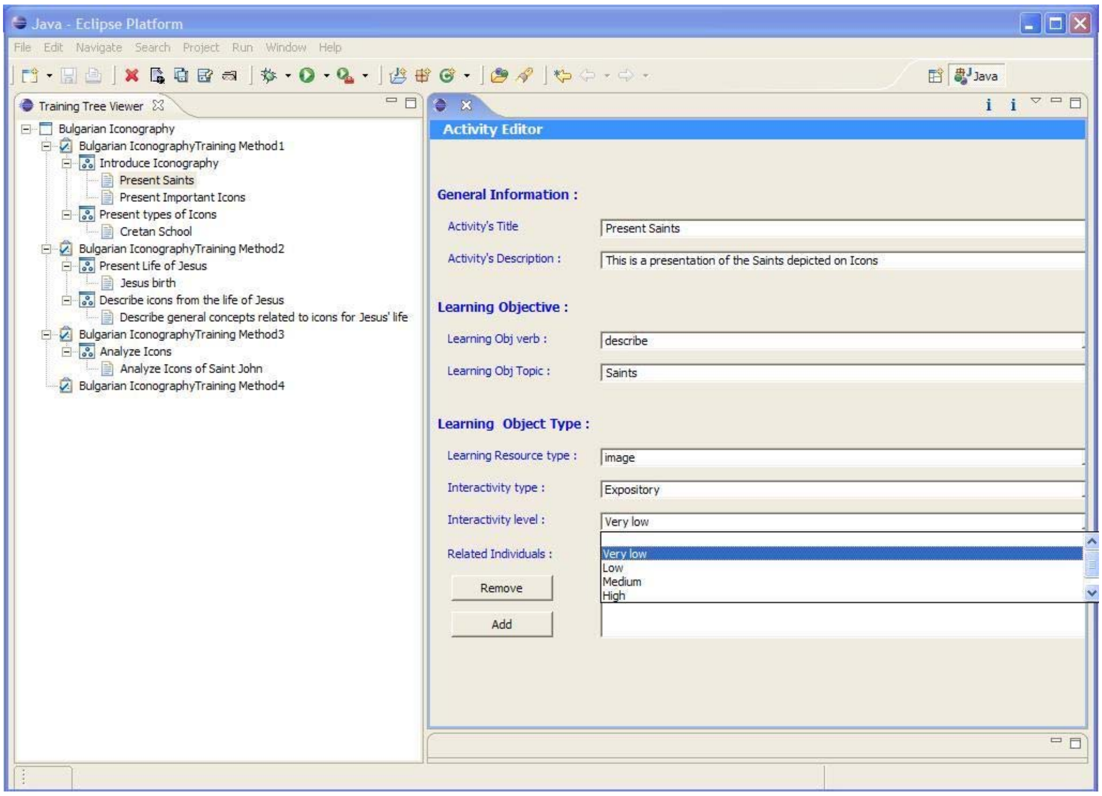

Figure 4. The Learning Designs Editor User Interface

3.3 Learning Objects

Current developments in eLearning have promoted the concept of reusable learning objects. Traditionally, learning was organized in lessons and courses covering predefined objectives. In eLearning environments the material is broken into smaller independent pieces that can be used as they are or in combination with other material to form higher level objects covering the learning needs of the users on demand and at the right time.

One important issue related to the concept of reusable learning objects is their description with metadata. The most popular metadata model used is the IEEE Learning Object Metadata (LOM) standard. It is possible to represent some pedagogical properties that can be matched with corresponding properties of Learner Profiles in order to support an automated process for the construction of personalized learning experiences. Several of the parameters mentioned in the previous section (e.g. difficulty, technical preferences, language, learning provider etc.) can be directly incorporated in LOM descriptions. However, as already mentioned, one of the most important aspects in personalization is the representation of Learning Objectives (also used to extract previous knowledge) that capture the intended learning outcome of learning objects which is not directly addressed in LOM. Other elements of LOM, such as keywords or description are usually used to describe Learning Objectives. These simple text descriptions do not represent a formal way for defining learning objectives. Consequently, this approach presents a technical barrier because textual descriptions are not machine-readable and cannot be exploited by personalization components.

To address the shortcoming described above we need to define a more formal and pedagogically-sound way of expressing Learning Objectives, as well as their representations based on appropriate adaptation of existing LOM elements. For this reason we use the previously mentioned Bloom's Taxonomy of educational objectives to define Learning Objectives as pairs consisting of a verb taken from a Bloom's taxonomy and a topic referencing a concept or individual of a domain ontology.

In LOM, Learning Objectives can be expressed following the above approach using its classification element. The classification element describes where a learning object falls within a particular classification system. To define multiple classifications, there may be multiple instances of this category. The following example shows how this element can be adapted in order to represent a specific Learning Objective.

```
<lom:classification>
  <lom:purpose>
    <lom:value>educational objective</lom:value>
    <!-- Each educational objective is defined as verb from Bloom's Taxonomy)+ Topic
(Ontology Concept/Individual) -->
  </lom:purpose>
  <lom:taxonPath>
    <lom:source>
      <lom:string language="en">http://somehost/bloomstaxonomy.owl</lom:string>
      <!-- The URL of the ontology containing the Bloom's Taxonomy Verbs-->
    </lom:source>
    <lom:taxon>
      <lom:entry>
        <lom:string language="en">explains </lom:string>
       <!-- The verb of the learning objective-->
      </lom:entry>
    </lom:taxon>
   </lom:taxonPath>

  <lom:taxonPath>
    <lom:source>
      <lom:string language="en">http://somehost/iconographyontology.owl</lom:string>
      <!-- The URL of the target ontology -->
    </lom:source>
    <lom:taxon>
      <lom:entry>
        <lom:string language="en">Iconographic Style</lom:string>
        <!-- The topic of the learning objective (a Concept of Iconography Ontology)-->
      </lom:entry>
    </lom:taxon>
   </lom:taxonPath>
 </lom:classification>
```

Educational level has been also considered as an important parameter when performing personalization. In order to be able to retrieve learning objects that are appropriate in terms of the educational level, this info should be incorporated in their descriptions. The only appropriate element of LOM that allows for the inclusion of educational levels is the classification element. The following example shows how the classification element of LOM is used in order to include info about the intended educational level of the current learning object:

```
<lom:classification>
  <lom:purpose>
    <lom:value>educational level</lom:value>
  </lom:purpose>
  <lom:taxonPath>
    <lom:source>
      <lom:string language="en">http://somehost/educationallevels.owl    </lom:string>
      <!-- The URL of the selected taxonomy of educational levels-->
    </lom:source>
    <lom:taxon>
      <lom:entry>
```

```
          <lom:string language="en">Primary</lom:string>
          <!-- The educational level for which this learning object is appropriate-->
        </lom:entry>
      </lom:taxon>
    </lom:taxonPath>
</lom:classification>
```
Fig. 3. Use of classification element of LOM to represent Educational Level.

3.4 Personalization Component

The Personalization Component takes into account the knowledge provided by the Learning Designs and the Learner Profiles and constructs personalized learning experiences that are delivered next to eLearning applications in an appropriate form (e.g. as a SCORM package). Specifically, the goal is to find an appropriate Training Method of a Learning Design that will be used thereafter to construct a learning experience adapted to the Learner's needs. As already mentioned, learning objects are bound to the learning scenario at run-time.

The procedure of constructing an adaptive learning experience is illustrated in Figure 5. In each step several parameters of the Learner Profile (given in brackets in Figure 5) are taken into account:

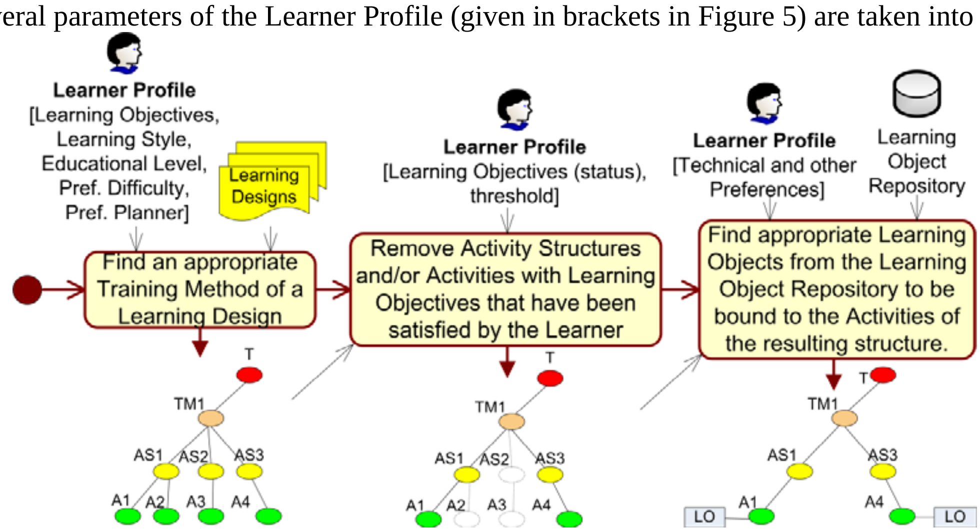

Figure 5. The procedure of dynamic construction of personalized learning experiences

Step 1

At the beginning, the component tries to find an appropriate Training Method of a Learning Design taking into account the Learner's Goals, Learning Style, Educational Level, preferred Difficulty, and preferred Planner. To do so, the existing Training Methods are ranked using the following formula:

$$w_{TM} = a_{LV} \cdot w_{LV} + a_{LS} \cdot w_{LS} + a_P \cdot w_P + a_D \cdot w_D$$

Where: $a_{LV} + a_{LS} + a_P + a_D = 1$

w_{LV} is a weight in [0,1] representing the degree of satisfaction Learner's Learning Goals from the Learning Objectives associated (indirectly) with the Training Method. That includes the Learning Objective of its parent Training and the Learning Objectives of its Activity Structures and Activities. This weight is computed as follows:

$w_{LV} = \frac{\sum_{i=1}^{n} p_i}{n}$, where $p_1, ..., p_n$ are the priorities of the Learning Goals of the Learner taking into account only those Learning Goals that correspond to Learning Objectives associated with the Training Method.

w_{LS} is 1 if the Training Method's associated Learning Style matches the Learning Style of the Learner and 0 otherwise. Note that depending on the taxonomy of Learning Styles used, we may have similarities between different Learning Styles. In that case, these similarities can be used to compute this weight.

w_P is 1 if the Training Method's Planner (i.e. the one associated with its parent Training) is one of the Learner's preferred Planners and 0 otherwise.

w_D is a weight in [0,1] representing the degree of similarity between the Difficulty of the Training Method and the Learner's preferred Difficulty. To compute this weight, we assume that the different (ordered) textual values of Difficulty are mapped to [0,1] so that higher Difficulty values are closer to 1. The simplest way to achieve this is to map the lowest difficulty to 0, map the higher difficulty to 1 and all intermediate values are mapped uniformly in [0,1] with distance between two successive values equal to 1/(n-1) where n is the total distinct Difficulty values. Then, w_D can be computed as follows:

$$w_D = 1 - \left(\left| d_P - d_{TM} \right| + d_P \cdot f\left(d_{TM} - d_P\right) \right)$$

where d_P is the preferred Difficulty of the Learner (the one stored in his profile), d_{TM} is the difficulty of the Training Method, and f is a function defined as $f = \begin{cases} 0, & x \le 0 \\ 1, & x > 0 \end{cases}$.

The above formula is based on the assumption that Difficulty levels that are lower than the preferred Difficulty of the Learner are more appropriate than higher Difficulty levels.

Step 2

When an appropriate Training Method is found its structure is further refined, by removing from it Activity Structures and Activities with Learning Objectives that have been satisfied by the Learner (the Learner can define a threshold value t, so that Learning Objectives with satisfaction value greater than t are considered as satisfied).

Step 3

Finally, appropriate learning objects are retrieved and bound to each node (Activity) of this structure constructing the learning experience. For each Activity, all Learning Objects having the Activity's Learning Objective are retrieved and then they are ranked using the following formula:

$$w_{LO} = \frac{w_{EL} + w_L + w_{CP} + w_{LRT} + w_{IT} + w_{IL}}{6}$$

Where:

w_{EL} is 1 if the Educational Level of the Learning Object is the same as the Educational Level of the Training Method selected in step 1 and 0 otherwise

w_{L} is 1 if the Language of the Learning Object is the same as the preferred Language of the Learner and 0 otherwise

w_{CP} is 1 if the Content Provider offering the Learning Object is one of the Learner's preferred Content Providers and 0 otherwise

w_{LRT} is 1 if the Learning Resource Type of the Learning Object is the same as the Learning Resource Type of the Activity and 0 otherwise

w_{IT} is 1 if the Interactivity Type of the Learning Object is the same as the Interactivity Type of the Activity and 0 otherwise

w_{IL} is 1 if the Interactivity Level of the Learning Object is the same as the Interactivity Level of the Activity and 0 otherwise

Note that the above six (6) weights correspond to a Boolean approach. We could use a more sophisticated approach where weights can take any value in [0,1] to reflect similarities between values compared. E.g. if similarities between different Educational Levels are specified, this can be taken into account to compute w_{EL}. Moreover the formula above used to compute w_{LO} can be revised to correspond to a weighted sum instead of a simple average value.

4. EXPERIMENTAL EVALUATION OF THE PROPOSED PERSONALIZATION FRAMEWORK

In order to acquire preliminary evaluation data regarding our proposed personalization framework we have conducted a controlled experiment to find out if systems that follow our approach can perform better than other systems that offer the same (static) courseware to all learners.
We should note here that our controlled experiment has not been performed in a real-life situation (it is a laboratory experiment) nor does it compare our personalization approach to other personalization approaches. This will be done in LOGOS Project (http://www.logosproject.com) evaluation phase using its specified target user groups. The purpose of this preliminary experimentation is to validate the usefulness of our approach as opposed to one-fits-all solutions.

4.1 Experimental Setting

In order to evaluate our personalization system we have engaged a domain expert to manually construct a course about the "Sharable Content Object Reference Model (SCORM) eLearning standard" as (s)he would do if it was intended to teach this subject in a class. The expert following the teaching procedure that always uses constructed a structure of the topics to be taught along with appropriate learning material that is being associated with each topic.

We engaged the same domain expert to construct a learning design for teaching the same subject following our approach. That means that (s)he had to construct several abstract training scenarios (training methods) for teaching the same subject for some combinations of learning styles, educational level and difficulty (let's say {general to specific, further, high} and {example oriented, further, low}. In each activity (s)he has to specify the preferred learning object characteristics that (s)he considers to be appropriate to support the corresponding learning activity, without binding specific learning objects with activities.

We then selected 10 target learners with background in computer science but varying in their knowledge about eLearning standards and specifically SCORM. We separated those learners in two groups of 5 persons each. The first group attended the manually constructed course (control group), while each member of the second group (test group) had a personalized learning experience generated from our personalization system taking into account the specific educational needs of each learner. In order to classify the Learners with respect to the chosen Learning Style taxonomy we have used an appropriate questionnaire. Some indicative questions were:

"When considering a body of information, I am more likely to (a) focus on details and miss the big picture, (b) try to understand the big picture before getting into the details",

"Once I understand (a) all the parts, I understand the whole thing, (b) the whole thing; I see how the parts fit"

The following table summarizes the design of the experimentation conducted:

Table 1. Design of the experimentation

Purpose	Investigate the impact of personalization in the learning time needed by a learner to complete a course. Investigate the personalized learning outcomes and compare with a situation where no personalization is present (static courseware). Investigate the relationship between the learning effectiveness and personalization.
Objects	Computer Science and Computer Engineering graduates with varying knowledge about eLearning standards and specifically SCORM.
Range of experiment	Volunteers recruited from the postgraduate students and the staff working at the Department of Electronics and Computer Engineering Department at the Technical University of Crete. Random grouping of Learners.
Organization	1. Recruiting the volunteers 2. Planning the experimental time table 3. Actual experimentation 4. Analysis of results using certain metrics
Experimental time	Add up to 100 minutes for each learner. 1. Training on the experimentation process and objectives: 15 minutes 2. Pre-test: 10 minutes 3. Attending the course (personalized or not): up to 60 minutes; 4. Post-test: 15 minutes
Method	1. Grouping the ten learners into two groups randomly: five learners in each group (the first group does not attend a personalized course). 2. Training the learners in order to be able to use the software. 3. Classifying Learners in terms of their Learning Style using simple questionnaire. 4. Testing before learning. The score for each learner is recorded. 5. Learning by using learning system on computer. The learning time for each learner is recorded. 6. Testing after learning. The score for each learner is recorded.
Evaluation metrics	We compute the following metrics for both the control group and the test group: *ALT*: Average learning time. *ASR*: Average success rate (grade for the post-test normalized in [0, 1]). *ALE*: Average learning efficiency (ratio of success rate and learning time – success rate per minute). *ALT-PG*: Average learning time per pretest group. We define two groups of learners in both the control and the test group. The first contains those with high

	score in the pretest and the second those with a low-score in the pretest. *ASR-PG*: Average success rate per pretest group. We define two groups of learners the same way as in the ALT-PG metric. *ALE-PG*: Average learning efficiency (ratio of success rate in the post-test and learning time – success rate per minute) per pretest group. We define two groups of learners the same way as in the ALT-PG metric. *ALT-LS*: Average learning time per learning style. Both the control and the test group are divided into two groups depending on the learning style of learners. *ASR-LS*: Average success rate per learning style Both the control and the test group are divided into two groups depending on the learning style of learners. *ALE-LS*: Average learning efficiency per learning style (ratio of success rate and learning time – success rate per minute). Both the control and the test group are divided into two groups depending on the learning style of learners.

4.2 Experimental Results

Figure 6(a) shows the learning time needed to attend the learning experience. It is evident that without personalization (control group) the learning time is greater, which implies that personalization results in less required time for learning. Figure 6(b) shows the average success rate, i.e. the average grade that the learners receive in the test after the learning. It is evident again that with personalization (test group) the results are better meaning that personalized courses result in better learning effect by approximately 11%. In terms of learning efficiency, as shown in Figure 6(c), personalization has a stronger impact: 37% better results.

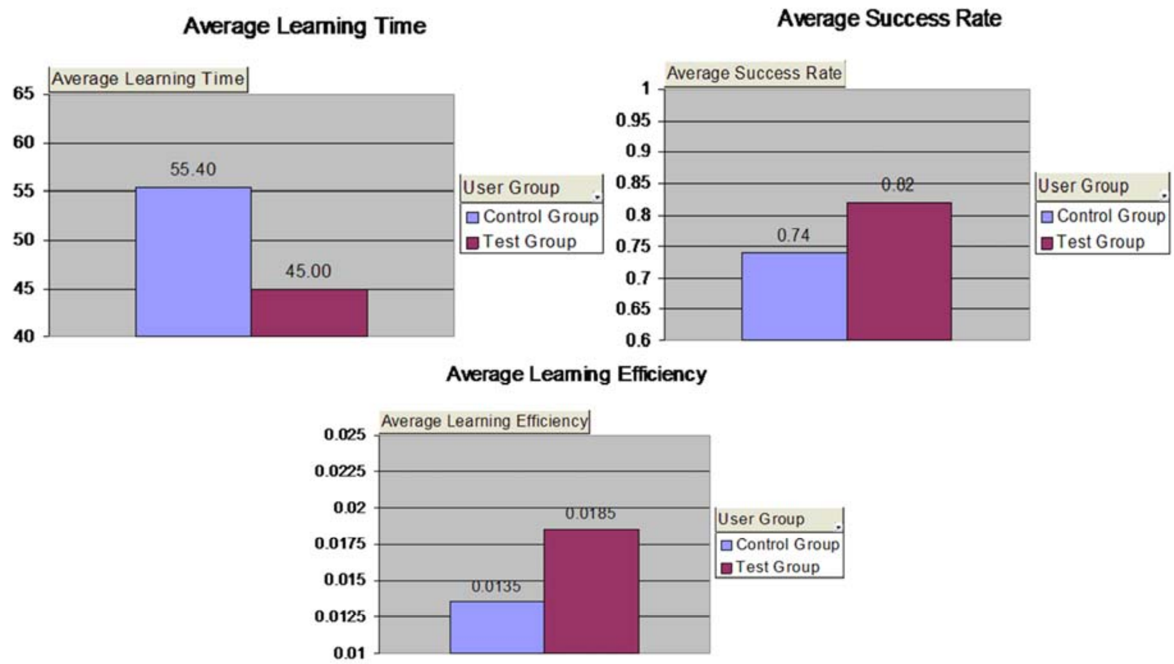

Figure 6. a) Average Learning Time in minutes, b) Average Success Rate normalized in [0,1], and c) Average Learning Efficiency computed as success rate per minute of learning time.

In order to evaluate the impact of personalization depending on the previous knowledge of learners, we have computed the three metrics presented in the following three figures using a grouping of learners with respect to their performance in the pretest. We have grouped them in two groups:

those with high score in the pretest (success rate 0.5 or higher) and those with low score in the pretest (success rate under 0.5). In terms of learning time (see Figure 7(a)) both low score and high score groups present similar improvement when personalization is employed with a slight antecedence of the high score group (21.65% improvement as opposed to 20.55% improvement for the low score group). In terms of success rate, the high score group performs better in comparison with the low score group (see Figure 7(b)). The high score group has 18.75% improvement while the low score group has a 12.30% improvement. The stronger impact of personalization in the high score group is even more evident when the learning efficiency metric is used (Figure 7(c)). The high score group has 51.63% improvement while the low score group has a 42.60% improvement. The higher impact of personalization in the high score group is justified by the fact that our personalization approach takes into account the previous knowledge of learner in order to create personalized courseware that contains only the necessary learning material to address the learning needs of the learner without repeating things that are already learned. This results in less learning time and better exploitation of the learning time.

The next thing that we investigated is the impact of learning style in the learning effect. We have grouped the learners in both the control and the test group into two groups. The first one contains the learners with learning style “general-to-specific”, i.e. the learners that learn better when they study first the general concepts about a certain topic and then study the details. The second group contains the learners that have “specific-to-general” learning style. Taking into account that the static courseware given to the control group has been designed following a principle-oriented approach, we expect to see a higher impact of personalization in the case of “specific-to-general” learning style. Indeed, the analysis of the experimental results (Figure 8(a),(b) and (c)) justifies this expectation.

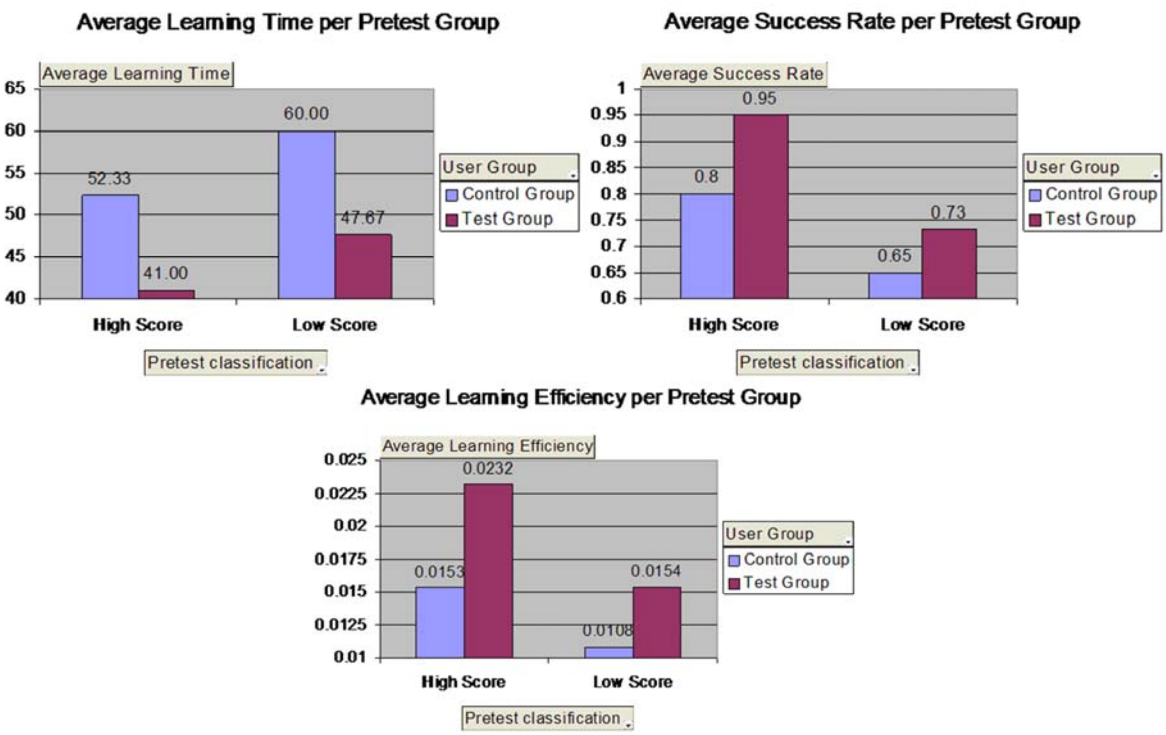

Figure 7. a) Average Learning Time, b) Average Success Rate normalized in [0,1], and c) Average Learning Efficiency computed as success rate per minute of learning time, for learners that received a high score in the pretest and for learners that received a low score in the pretest.

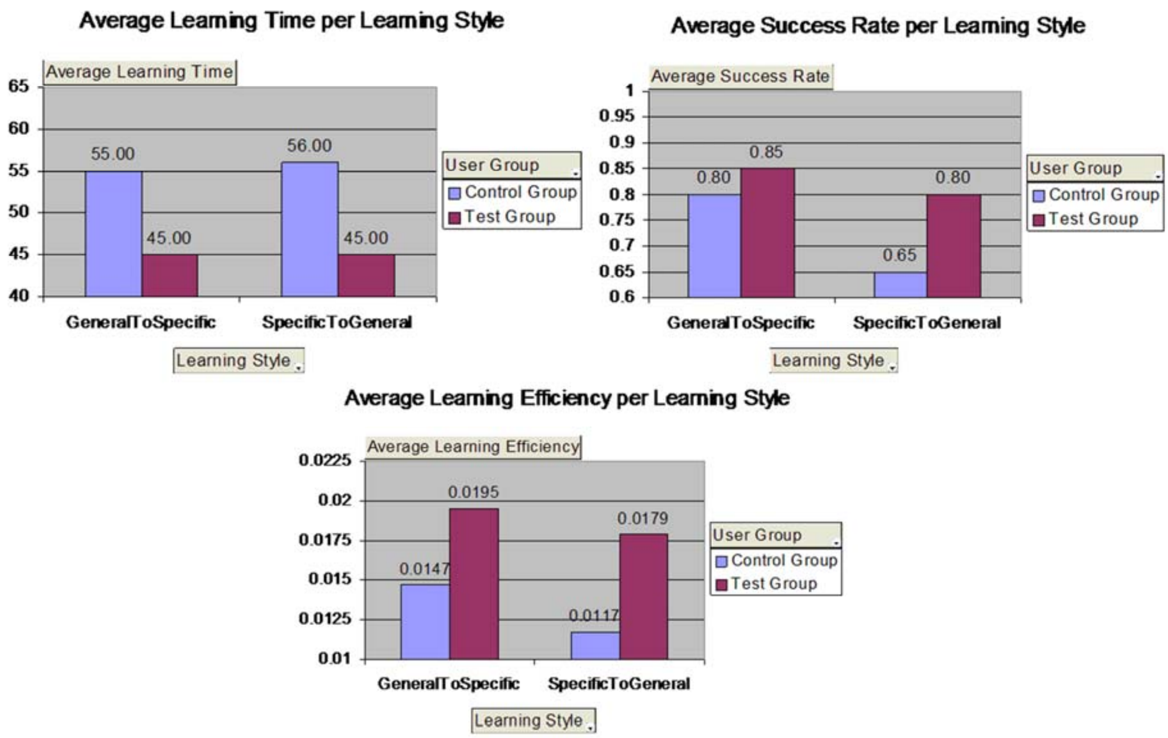

Figure 8. a) Average Learning Time per Learning Style of Learners, b) Average Success Rate normalized in [0,1] per Learning Style of Learners and c) Learning Efficiency (computed as success rate per minute of learning time) per Learning Style of learners.

5. RELATED WORK

Capuano et al. (2005) follow a similar approach is followed to represent pedagogy in order to support run-time resource binding. Our approach differs in that it takes into account the learning style, the educational level and learning goals of the Learners, supporting the representation of different learning paths (Training Methods) for training in a specific subject. In (Meisel, Compatangelo & Hörfurter, 2003), although the need for supporting different training methods for the same subject is recognized, these methods are not connected as in our approach with the learning styles and educational levels of the Learners. Moreover, description of appropriate learning objects characteristics beyond semantics is not supported. An alternative approach is presented in (Karampiperis & Sampson, 2004) regarding automatic course sequencing. In this work learning paths are not constructed based on pedagogical models, but are extracted from a directed acyclic graph that is the result of merging the knowledge space (domain model) and the media space (learning objects and their relation) using minimum learning time as an optimization criteria. However, since this approach is highly based on the domain model that does not necessarily imply an instructional model, and also on the relations of learning objects and their aggregation level, there is a risk that the result of the sequencing process may be not always “pedagogically-right” adapted to the Learners’ various learning styles.

6. CONCLUSION

This paper presented a personalization framework that allows for the dynamic creation of pedagogically-sound learning experiences taking into account the variety of the Learners and their individual needs. This framework defines a model for the representation of abstract training scenarios (Learning Designs) that clearly separates pedagogy from content allowing this way the construction of real personalized learning experiences where the Learners' needs are taken into account both in the selection of structure and content of the learning experience. This is possible, since learning objects are bound to the learning scenario at run-time taking into account information encoded in Learner Profiles. Experimental results show that the proposed framework can provide effective personalized learning experiences that reduce the learning time to achieve the desired learning outcomes thus increasing the learning efficiency compared with traditional "one size fits all" approaches.

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