



PALE 2011:  
PERSONALIZATION APPROACHES  
IN LEARNING ENVIRONMENTS

**International Workshop on  
Personalization Approaches  
in Learning Environments  
(PALE 2011)**

**in conjunction with the 19th edition of the User Modeling,  
Adaptation and Personalization Conference (UMAP 2011)**

**Girona, Spain  
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**Proceedings**

**Editors:**

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## PREFACE

The benefits of the personalization and adaptation of computer applications to each user have been widely reported in recent decades. Educational applications are not an exception, both in e-learning, i.e. the use of electronic media to teach or assess, and in b-learning (blended learning), i.e. to combine traditional face-to-face instruction with electronic media.

The International Workshop on Personalization Approaches in Learning Environments (PALE) is the result of merging the experience and background of three workshops focused on applying user modeling, personalization and adaptation in learning environments. Each of them has been organized as a learning café following the corresponding methodology and aiming to provide an answer to the question “*Which approaches can be followed to personalize learning environments?*” from different perspectives, as follows:

- **APLEC: Adaptation and Personalization in E-B/Learning using Pedagogic Conversational Agents.** It is focused on the open issues in interactive learning environments that build the knowledge with the student through a set of interactions, such as in natural language by using animated Pedagogic Conversational Agents (PCAs).
- **ROLE: Personalizing Responsive Open Learning Environments.** It is focused on the open issues in responsive open learning environments that permit personalization of the entire learning environment and its functionalities, i.e. individualization of its components and their adjustment or replacement by alternative solutions.
- **TUMAS-A: Towards User Modeling and Adaptive Systems for All.** It is focused on the open issues in inclusive learning environments to provide a personalized, accessible and ubiquitous support for their users (learners, facilitators, professors) using the appropriate technologies and standards as well as the evaluation procedures that can measure the impact of the personalized and inclusive support for all, but considering their individual and evolving needs, in their particular context.

The workshop will take place on 15<sup>th</sup> of July 2011, in Girona, Spain in conjunction with the International Conference on User Modeling, Adaptation and Personalization (UMAP). A blind peer-reviewed process by at least two reviewers with expertise in the area has been carried out. As a result, 12 submissions have been accepted. This volume contains the proceedings of the workshop organized according to the different learning cafés. We would like to thank the authors for their submissions, our Programme Committee members for their reviews and the UMAP workshop chairs for their advice and guidance during the PALE workshop organization.

June 2011

Dr. Diana Pérez-Marín  
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## **ADAPTATION AND PERSONALIZATION IN E-B/LEARNING (APLEC)**

APLEC is focused on the open issues in interactive learning environments that build the knowledge with the student through a set of interactions, such as in natural language.

# Processes in Learning

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**Abstract.** One can productively model the learner, the teacher, their dialog, and other factors that influence learning as statistical processes. For example, one can model a student as a machine that moves from state to state probabilistically, conditioned on teachers' actions and other learning events. Models can be personalized by fitting their parameters with data from individuals, or models might represent groups of learners that are specified a priori or emerge from clustering. Given models of learning, one can use data gathered in online teaching/learning systems to optimize learning. I will describe three efforts in the University of Arizona School of Information to model aspects of learning statistically: Teaching robots the meanings of verbs by demonstrating the verb; teaching softbots plans through dialog with ordinary people; and the undesirable (and unintended!) consequences of inadequate personalization of tutoring in a conventional intelligent tutoring system.

# Understanding How Humans Teach Robots

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**Abstract.** Robots and other intelligent devices capable of carrying out highly complex procedures are becoming ubiquitous in the home and workplace. However, changing the behavior and capabilities of these devices typically requires direct programming by specially trained engineers. While machine learning (ML) algorithms offer the allure of allowing machines to improve their knowledge and behavior from experience, ML algorithms still require considerable expertise to use in practice. To bridge this gap, human-instructable computing seeks to develop intelligent devices that can be taught by natural human instruction. Our research focus is on developing methods for non-expert humans to teach complex behaviors to autonomous agents by accommodating natural forms of human teaching. Currently, most systems for human-robot teaching allow only one mode of teacher-student interaction (e.g., teaching by demonstration or feedback), and teaching episodes have to be carefully set up by an expert. To understand how we might integrate multiple, interleaved forms of human instruction into a robot learner, we performed a behavioral study in which untrained humans were allowed to freely mix interaction modes to teach a simulated robot (secretly controlled by a human) a complex task. We found that teaching styles varied considerably but can be roughly categorized based on the types of interaction, patterns of testing, and general organization of the lessons given by the teacher. Analysis of transcripts showed that human teachers often give instructions that are nontrivial to interpret and not easily translated into a form useable by ML algorithms. In particular, humans often use implicit instructions, fail to clearly indicate the boundaries of procedures, and tightly interleave testing, feedback, and new instruction. Our study contributes to a better understanding of human teaching patterns, highlights the challenges of building an initial automatic teacher interpretation system using ML algorithms and makes specific recommendations for future human-robot interaction systems.

# Automatic generation of questions adapted to the personality and learning style of the students

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**Abstract.** Students learn according to different learning styles. Moreover, they have different personality features. However, it is usually the case that they are always asked in the same way, irrespectively of their learning style or personality. In this paper, we present a procedure to automatically generate the questions of e-learning tests adapted to the learning style and personality of each student. It is our hypothesis that it will facilitate the assessment and students will be able to perceive that the generated questions are easier to understand and answer. A preliminary experiment with 10 students seems to provide evidence to support that hypothesis.

**Keywords:** conversational agent, learning style, personality, e-learning

## 1 Introduction

In our previous work, we have focused on the possibility of adapting the dialogue to the student knowledge [1], that is, extracting information from the students' answers to e-learning systems to generate dialogues based on the concepts identified as less known by the students.

In this paper, we consider that the adaptation should not be just limited to the student knowledge, but that it is essential to take also into account the learning style of the student and the features of his/her personality. In particular, even when the adaptation to the student knowledge has identified that it is necessary to ask a question about a concept, it is our insight that the generated question can be furtherly adapted automatically so that different students get different questions.

For instance, if a conversational agent has identified that the student does not know the concept *thread* in Operating Systems. It could always generate the basic question: What is a *thread*? to start the educational dialogue on learning the concept, or, it could generate different questions depending on the learning style and personality of the student such as "Tell me about *threads*" if the student has an active personality, or show the student a visual image of a *thread* and ask him/her what the image represents if the learning style is visual.

It is our hypothesis that this will facilitate the assessment and students will be able to perceive that the generated questions are easier to understand and answer. Therefore, we have devised a procedure to automatically generate the questions of e-learning tests adapted to the learning style and personality of each student. A

preliminary experiment with 10 students seems to provide evidence to support that hypothesis. Moreover, the results achieved can be useful to give more insight into the study of how an effective conversation between the student and the agent look like.

## 2 Procedure

The proposed procedure follows these steps:

- 1) The student completes the Solomon-Felder learning styles test [2].
- 2) The student completes the Big Five personality test [3].
- 3) The teacher introduces a set of questions (the original questions, X).
- 4) New questions are generated according to several proposed patterns for each Solomon-Felder learning style and/or each of the Big Five personality features.
- 5) The student is asked the question adapted to his/her Solomon-Felder learning style and personality according to the tests.

The reason why these tests have been chosen is because they are quite common and accepted in their areas. In particular, the Solomon-Felder learning styles test identifies that a student can be:

- **Active:** the student understands better direct and short information. Therefore, the question generated for this type of student will be direct and short. For instance, “Tell me about X”.
- **Passive:** the student prefers to think about the information on his/her own to process it. Therefore, the question generated for this type of student will make the student think. For instance, “Think about X” or “Take you time and then, tell me about X”.
- **Perceptive:** the student prefers to have facts that can sense. Therefore, the question generated for this type of student will be based on facts. For instance, “How do you see X?”.
- **Intuitive:** the student prefers to identify relationships. Therefore, the question generated for this type of student will be based on relationships. For instance, “It is evident that X”.
- **Visual:** the student prefers to see the information. Therefore, the question generated for this type of student will be based on images. For instance, “Imagine the following image, and then X”.
- **Verbal:** the student prefers to listen to the information. Therefore, the question generated for this type of student will be based on sounds. For instance, “Write about X”.
- **Global:** the student prefers to see all the connections in general, without focusing on the details. Therefore, in this case, the adaptation is not at the level of one question, but the program should show all the questions.
- **Sequential:** the student prefers to see the questions one by one in sequence. Therefore, as in the previous case, the adaptation is not at the level of one question, but the program should allow to show the questions one by one.

The Big Five personality test identifies that a student can be:

- **Extrovert:** the student has features such as talkative, assertive, happy.... Therefore, the question generated for this type of student will allow him/her to think that s/he is talking to a lot of people. For instance, “What would you say or a lot of people about X?”.
- **Introvert:** the student has features such as quiet, shy, reserved...Therefore, the question generated for this type of student will allow him/her to talk to him/herself. For instance, “For you, what about X?”.
- **Cordiality:** the student is pleasant, nice, likeable,... Therefore, the question generated for this type of student will allow him/her to talk to him/herself. For instance, “Could you help with X?”.
- **Antipathy:** the student is cold, unpleasant, distant, grumpy,...Therefore, the question generated for this type of student will allow him/her to have a cold challenge. For instance, “I am sure you are not able to talk about X”.
- **Responsibility:** the student is responsible, dependable, trustworthy... Therefore, the question generated for this type of student will ask him/her to help other people. For instance, “If you have to explain X to a friend, what would you say to him/her?”.
- **Disorganized:** the student is careless, neglected, forgetful...Therefore, the question generated for this type of student will help him/her to focus on the question. For instance, “X, what is it?”.
- **Emotional stability:** the student is constant, peaceful, tranquil... Therefore, the question generated for this type of student will ask him/her to help other people. For instance, “In the context of Y, what about X?”.
- **Neuroticism:** the student is anxious, nervous, worried...Therefore, the question generated for this type of student will try to keep him/her calm. For instance, “If you are asked about X, although you are not forced to answer, what would you say?”.
- **Open-minded:** the student has general interests, and s/he is imaginative, original, creative... Therefore, the question generated for this type of student will try to make him/her think open. For instance, “In general, imagine X, what can you say?”.
- **Convencionalism:** the student is ordinay, simple, superficial,...Therefore, the question generated for this type of student will narrow the possibilities down to a certain context. For instance, “According to Y, what can you say about X?”.

Figure 1 shows a snapshot of the procedure implemented in Flayer.

### 3 Discussion

Table 1 gathers the results of a preliminary experiment in which 10 students were asked to complete the tests and evaluate the generated questions. The experiment took 2 hours, after which they were asked two questions: if they have perceived the adaptation by showing them the original and generated questions adapted to their styles, and which their general opinion about the procedure was.



**Figure 1.** Snapshot of Flayer (on the left the styles, on the right the counter of questions generated and checked, above the original question ‘Which are the type of skills that a child can develop during his life?’, and below the generated question for a perceptive student ‘How do you see that are the type of skills that a child can develop during his life?’ with some buttons to modify, insert, delete or accept the question, and to log out).

**Table 2.** Results of the preliminary experiment

Student	Has s/he perceived the adaptation?	General opinion
1	Sometimes	I do not like it
2	Sometimes	It is interesting
3	Sometimes	It is interesting
4	Yes	It is good
5	Yes	It is interesting
6	Sometimes	It is good
7	Yes	I do not care
8	Sometimes	It is interesting
9	Yes	I do not like it
10	Yes	I do not care

As can be seen, all the students have perceived the adaptation sometimes, and 50% of them have always perceived it. In general, 60% of the students consider that the procedure is interesting or good, 20% do not care, and 20% dislike it because they would rather not take tests on their personality or learning style.

As future work, we would like to keep exploring the possibilities of the adaptation with different patterns and to study if the adaptation has some impact on the learning.

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3. Big Five personality test, available on-line at <http://es.outofservice.com/bigfive/?srclang=en>

# Social Robots in Learning Environments: a Case Study of an Empathic Chess Companion

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**Abstract.** We present a scenario where a social robot acts as a chess companion for children, and describe our current efforts towards endowing such robot with empathic capabilities. A multimodal framework for modeling some of the user’s affective states that combines visual and task-related features is presented. Further, we describe how the robot selects adaptive empathic responses considering the model of the user’s affect.

**Keywords:** learning companions, empathy, affective user modeling.

## 1 Introduction

In the last few years, there has been a growing interest in developing animated pedagogical agents for learning environments [13]. Several studies suggest that pedagogical agents positively affect the way students perceive the learning experience due to their non-verbal behaviours [13], physical appearance or voice [5]. More recently, the ability to recognise and respond to the student’s affective state has also been considered a very important characteristic of pedagogical agents [4]. In humans, the capacity of understanding and responding appropriately to the affective states of others is commonly designated as empathy [6]. Several theorists argue that empathy facilitates the creation and development of social relationships [1]. A positive student-teacher relationship increases student’s trust, cooperation and motivation during the learning process. For these reasons, empathy is often linked with effective teaching.

Research on artificial companions has recently started to address the issue of designing systems for the automatic recognition of scenario-dependent, spontaneous affect-related states. Examples include the system by Kapoor et al. [8], which can automatically predict frustration, and the work by Nakano and Ishii [14] to estimate the user’s conversational engagement with a conversational agent. In this domain, there has been an increasing attention towards systems utilising contextual information to improve the affect recognition performance [9]. In our previous work on the automatic detection of engagement, we showed that a combination of task and visual features allows for the highest recognition

rate to be achieved [3]. While many efforts are being made to detect user’s affective and motivational states, another branch of research addresses the challenge of how affect-aware agents should react to those states, and in which ways empathic responses improve the interaction. For example, Robison et al. studied the impact of affective feedback on students interacting with a virtual agent in a narrative-centered learning environment [16]. In another study, Saerbeck and colleagues [17] investigated the effects of a robot’s social supportive behaviour on student’s learning performance and motivation.

In this paper, we summarise our efforts on the development of a social robot with empathic capabilities that acts as a chess companion for children. By endowing the robot with empathic capabilities, we expect to improve the relationship established between children and the robot, which can ultimately lead them to improve their chess abilities. Thus, to behave empathically, our robot needs to (1) *model* the child’s affective states and (2) *adapt* its affective and prosocial behaviour in response to the affective states of the child. In the remaining of the paper, we present our approach for modelling empathy in a robotic learning companion.

## 2 Towards an Empathic Chess Companion

Our application scenario consists of an iCat robot that plays chess with children using an electronic chessboard (see Fig. 1). The iCat provides feedback on the children’s moves by employing facial expressions determined by the robot’s affective state. Chess can be considered an educational game, as it helps children develop their memory and problem solving skills [7]. A previous study using this scenario showed that the affective behaviour expressed by the iCat increased user’s perception of the game [10]. However, in another study, after several interactions children started realising that the robot’s behaviour did not take into account their own affective state [11]. The results of this study suggested that social presence decreased over time, especially in terms of perceived affective and behavioural interdependence. These dimensions refer to the extent to which users believe that the behaviour and affective state of the robot is influenced by their own behaviour and affective state. As described earlier, empathy requires the ability of understanding the user’s affective state and responding accordingly. Thus, in the remaining of this section, we describe our current research in these two distinct processes of empathy.



Fig. 1: Child playing with the iCat.

## 2.1 Modelling the User’s Affective State

Off-line analysis of videos recorded during several interactions between children and the iCat showed that children display prototypical emotional expressions only occasionally. Therefore, we aim to endow the robot with the ability to infer scenario-dependent user affective states, and specifically affective states related to the game and the social interaction with the robot: *valence of feeling* (positive or negative) and *engagement with the robot*. The valence of the feeling provides information about the overall feeling that the user is experiencing throughout the game, whereas engagement is “the value that a participant in an interaction attributes to the goal of being together with the other participant(s) and continuing the interaction”, as defined by Poggi [15]. In our previous work, we showed the key role of a subset of user’s non-verbal behaviours and contextual features in the discrimination of affective states [2, 3].

## 2.2 Adaptive Empathic Responses

After modelling the affective state of the user, the robot should be able to select the empathic responses that are most effective to keep the user in a positive affective state. Several empathic and pro-social strategies existing in the literature are being considered, such as facial expressions, verbal comments to encourage the player and game-related actions (e.g., allow the user to take back a bad move). Some of these strategies were proven to be successful in a previous study that investigated the influence of empathic behaviours on people’s perceptions of a social robot [12].

But how should the robot decide, among the set of possible empathic strategies, which one is more appropriate at a certain moment? We are currently implementing an adaptive approach, where the robot learns the best strategies for a particular user by estimating the success of an empathic strategy measuring the user’s affective state right after such strategy is displayed by the iCat. For example, consider a situation where the user is experiencing a negative feeling for loosing an importance piece in the game and the iCat responds with an encouraging verbal comment. If the user’s valence changes from negative to positive, then utterances containing encouraging behaviours will become part of the user’s preferences in that particular situation. As the same users are expected to interact with the robot for several games, the preferences for a particular user are updated even over different interaction sessions.

## 3 Discussion

In this paper, we described our work towards endowing the robot with empathic capabilities. A multimodal system for predicting and modeling some of the children’s affective states in real time is currently being trained using a corpus with videos previously collected in another experiments using this scenario. With this model of the user, we intend to personalise the learning environment by adapting the robot’s empathic responses to the particular needs of the child who is interacting with the robot.

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## **PERSONALIZING RESPONSIVE OPEN LEARNING ENVIRONMENTS (ROLE)**

ROLE is focused on the open issues in responsive open learning environments that permit personalization of the entire learning environment and its functionalities, i.e. individualization of its components and their adjustment or replacement by alternative solutions.

# Context-Aware Factorization for Personalized Student's Task Recommendation

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**Abstract.** Collaborative filtering - one of the recommendation techniques - has been applied for e-learning recently. This technique makes an assumption that each user rates for an item once. However, in educational environment, each student may perform a task (problem) several times. Thus, applying original collaborative filtering for student's task recommendation may produce unsatisfied results. We propose using context-aware models to utilize all interactions (performances) of the given student-task pairs. This approach can be applied not only for personalized learning environment (e.g., recommending tasks to students) but also for predicting student performance. Evaluation results show that the proposed approach works better than the none-context method, which only uses one recent performance.

## 1 Introduction

Recommender systems have been applied for e-learning task recently [1, 2]. One of the techniques, for instance, is collaborative filtering, e.g. k-nearest neighbors (k-NN) or matrix factorization, which takes into account just the last rating of users, i.e. it assumes that a user rates an item once. However, in educational environment, for example, recommending tasks (or problems or exercises) to students, this assumption might not hold since each student can perform the task several times. Furthermore, recommender system for educational purposes is a complex and challenging research direction since the preferred learning activities of students might pedagogically not be the most adequate and recommendations in e-learning should be guided by educational objectives, and not only by the user's preferences [3-5].

On the other hand, recommendation techniques have also been applied for predicting student performance recently [2, 6]. Concretely, [6] proposed a temporal collaborative filtering approach to automatically predict the correctness of students' problem solving in an intelligent math tutoring system. This approach utilized multiple interactions for a student-problem pair by using k-NN method; [2] proposed using matrix and tensor factorization to take into account the "slip" and "guess" latent factors as well as the temporal effect in predicting student performance.

Previous work [2] pointed out that an approach which uses student performance prediction for the recommendation of e-learning tasks could tackle the above

mentioned problems since we can recommend the tasks to the students based on their performance but not on their preferences. Using this approach, one can recommend similar tasks (exercises) to students and can determine which tasks are notoriously difficult for a given student. For example, there is a large bank of exercises where students lose a lot of time solving problems which are too easy or too hard for them. When a system is able to predict students' performance, it could recommend more appropriate exercises for them. Thus, we could filter out the tasks with predicted high performance / confidence since these tasks are too easy, or filter out the tasks with predicted low performance (too hard) or both, depending on the goals of the e-learning system [2].

This work proposes using context-aware models for student's task recommendation which utilize multiple interactions (performances) of a given student-task pair. This approach can be applied not only for predicting student performance as in [2] but also for personalized task recommendation to students. Here, we have not focused on building a real system, but on how to model the student's task recommendation using context-aware approach [7].

## 2 Data sets and Methods

In this section we first introduce the data sets. We then present the method without taking into account the context (considered as a baseline) and the proposed context-aware methods.

### 2.1 Data sets

Two data sets are collected from the KDD Challenge 2010 ([pslclatashop.web.cmu.edu/KDDCup](http://pslclatashop.web.cmu.edu/KDDCup)), which will be called "Algebra" and "Bridge" for short. We aggregated these data sets to get four attributes: student ID ( $s$ ), problem ID ( $i$ ), problem view ( $v$ ) which tracks how many times the student has interacted with the problem, and performance  $p$  ( $p \in [0..1]$ ) which is an average of successful solutions (averaging from "correct first attempt" attribute).

As described in the literature [8, 2], these data sets can be mapped to user-item-rating in recommender systems. In this case, students become users and problems become items which are presented in a matrix ( $s, i$ ) as in Figure 1a. In this work, the context ("problem view" -  $v$ ) is taken into account, thus, each data set is presented in a three-mode tensor ( $s, i, v$ ) as illustrated in Figure 1c.

### 2.2 Baseline (Without Using Context)

Traditional collaborative filtering has an assumption that each user rates for each item once, which means that only the last rating is used. Similarly, in this work, the last performance  $p$  of a student-problem pair ( $s, i$ ) is used (which ignores the multiple interactions between students and problems) and finally, a matrix factorization model

is applied. The following paragraph briefly summarizes the matrix factorization method (please see the article [2] for more details).

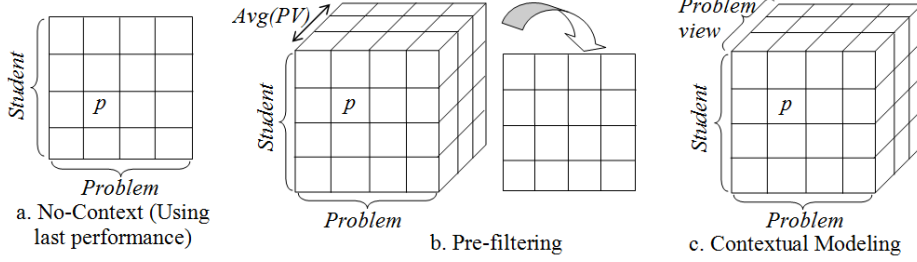


Fig. 1: An illustration of No-Context vs. Context-aware approach

Matrix factorization is the task of approximating a matrix  $\mathbf{X}$  by the product of two smaller matrices  $\mathbf{W}$  and  $\mathbf{H}$ , i.e.  $\mathbf{X} \sim \mathbf{WH}^T$  [9]. In the context of recommender systems the matrix  $\mathbf{X}$  is the partially observed ratings matrix,  $\mathbf{W} \in \mathbb{R}^{S \times K}$  is a matrix where each row  $s$  is a vector containing  $K$  latent factors describing the student  $s$  and  $\mathbf{H} \in \mathbb{R}^{I \times K}$  is a matrix where each row  $i$  is a vector containing  $K$  latent factors describing the problem  $i$ . Let  $w_{sk}$  and  $h_{ik}$  be the elements of  $\mathbf{W}$  and  $\mathbf{H}$ , respectively, then the performance given by a student  $s$  to a problem  $i$  is predicted by:

$$\hat{p}_{si} = \sum_{k=1}^K w_{sk} h_{ik} = (\mathbf{WH}^T)_{s,i} \quad (1)$$

where  $\mathbf{W}$  and  $\mathbf{H}$  are model parameters which can be obtained by an optimization process using either stochastic gradient descent or Alternating Least Squares [10] given a criterion such as Root Mean Squared Error (RMSE) or Mean Absolute Error (MAE).

### 2.3 Context-Aware Methods

We make use of two context-aware methods: “*Pre-filtering*” and “*Contextual Modeling*” [7] (in this work we use matrix and tensor factorization approach instead of heuristic-based and model-based approaches as in [7]).

**Pre-filtering (PF):** As its name, this method requires pre-processing on the data sets. To do this, the performance  $p$  is aggregated (averaged) along the context  $v$ . Thus, the three-mode tensor  $(s, i, v)$  now becomes the matrix as illustrated in Figure 1b.

After the pre-filtering step, we apply the matrix factorization method to factorize on student-problem pairs  $(s, i)$  as described in section 2.2.

**Contextual Modeling (CM):** In this method, the context  $v$  is preserved, thus, we have to deal with the three-mode tensor. Given a tensor  $\mathbf{Z}$  of size  $S \times I \times V$ , where the first and the second mode describe the student and the problem as in previous sections; the third mode describes the context (problem view -  $v$ ) with size  $V$ . Then  $\mathbf{Z}$  can be written as a sum of rank-1 tensors, using CANDECOM-PARAFAC [10]:

$$Z = \sum_{k=1}^K \lambda_k w_k \circ h_k \circ q_k \quad (2)$$

where  $\circ$  is the outer product,  $\lambda_k$  is a vector of scalar values, and each vector  $w_k \in \Re^S$ ,  $h_k \in \Re^I$ , and  $q_k \in \Re^V$  describes the latent factors of student, problem, and context, respectively. With this approach, the performance of student  $s$  for problem  $i$  at context  $v$  (problem view) is predicted by:

$$\hat{p}_{siv} = \sum_{k=1}^K \lambda_k w_{sk} h_{ik} q_{vk} \quad (3)$$

**“Student bias/effect” and “problem bias/effect”:** As shown in the literature [11, 8, 2], the prediction result can be improved if one incorporates the biased terms to the model. In educational setting, those biased terms are “student bias/effect” which models how good/clever a student is (i.e. how likely is the student to perform a problem correctly), and “problem bias/effect” which models how difficult/easy the problem is (i.e. how likely is the problem in general to be performed correctly) [2].

With these biases, the performance  $p$  in the pre-filtering method becomes

$$\hat{p}_{si} = \mu + b_s + b_i + \sum_{k=1}^K w_{sk} h_{ik} \quad (4)$$

and the performance  $p$  in the contextual modeling method (equation 3) becomes

$$\hat{p}_{siv} = \mu + b_s + b_i + \sum_{k=1}^K \lambda_k w_{sk} h_{ik} q_{vk} \quad (5)$$

where  $\mu$  is global average,  $b_s$  is student bias, and  $b_i$  is problem bias (how to obtain these values is already described the article [2]).

After the prediction phase, we can filter out the tasks with predicted high performance since these tasks are too easy, or filter out the tasks with predicted low performance (too hard) or both, depending on the goals of the e-learning system. Thus, the appropriate tasks can be delivered to students.

### 3 Experiments

We describe the experimental setting and then we present the comparison results.

#### 3.1 Experimental setting

We use just the first 5,000 problems in both Algebra and Bridge data sets. We use 3-fold cross-validation and paired t-test with significance level 0.05 for all experiments. We do hyper parameter search to determine the best hyper parameters for all methods. The Matlab Tensor Toolbox is used for experimenting ([csmr.ca.sandia.gov/~tgkolda/TensorToolbox](http://csmr.ca.sandia.gov/~tgkolda/TensorToolbox)).

### 3.2 Experimental results

Table 1 presents the mean absolute error (MAE) of the context-aware methods (PF and CM) which take into account the multiple interactions of student-problem pairs versus the baseline (without using context).

The PF and CM outperform the baseline method even though we have not used the bias terms. Employing student-problem biases to the models, the context-aware methods have statistically significantly improved to the baseline (on Algebra data set), and the PF method has promising results compared to the others. Without using biased terms, the result of CM is slightly better than PF.

Clearly, from these results we can see that the context-aware methods are suitable for taking into account the multiple interactions between students and problems. Thus, this approach can be a reasonable choice for personalized learning environment, especially recommending tasks (or problems or exercises) to the students.

**Table 1.** Mean absolute error of the Baseline vs. Context-Aware Methods

Data set	Baseline	Context-Aware Methods			
		PF	PF-Bias	CM	CM-Bias
Algebra	0.247±0.015	0.239±0.017	<b>0.188±0.015</b>	0.239±0.016	0.233±0.012
Bridge	0.193±0.033	0.185±0.030	<b>0.150±0.023</b>	0.183±0.030	0.170±0.024
Average	0.220	0.212	<b>0.169</b>	0.211	0.202

*PF: Pre-Filtering; CM: Contextual Modeling;  
Algebra and Bridge-to-Algebra from 2008-2009 data sets*

Moreover, the MAE improvements in the prediction models implicitly mean that the system can recommend the “right” tasks (exercises) to the students, and thus, we can help them reducing their time and effort in solving the tasks by filtering the ones that are too easy or too hard for them. Using these context-aware models, we can generate the performance for a given student-task pair, so the remaining works are wrapping around with an interface to deliver the recommendations. However, this work is out of the scope of this paper, and is leaved for future work.

## 4 Conclusion

We proposed using context-aware models to utilize all performances (interactions) of the given student-task pairs. We have shown that these methods can improve the prediction results compared to the none-context method, which only uses the last performance. This approach can apply not only for personalized recommending the tasks to students but also for predicting student performance.

It is well-known that factorization methods outperform the k-NNs collaborative filtering [12]. However, the comparison of the context-aware factorization methods with the temporal collaborative filtering (using k-NNs as in [6]) is leaved for future work.

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# Epistemic Beliefs and Open Learner Models

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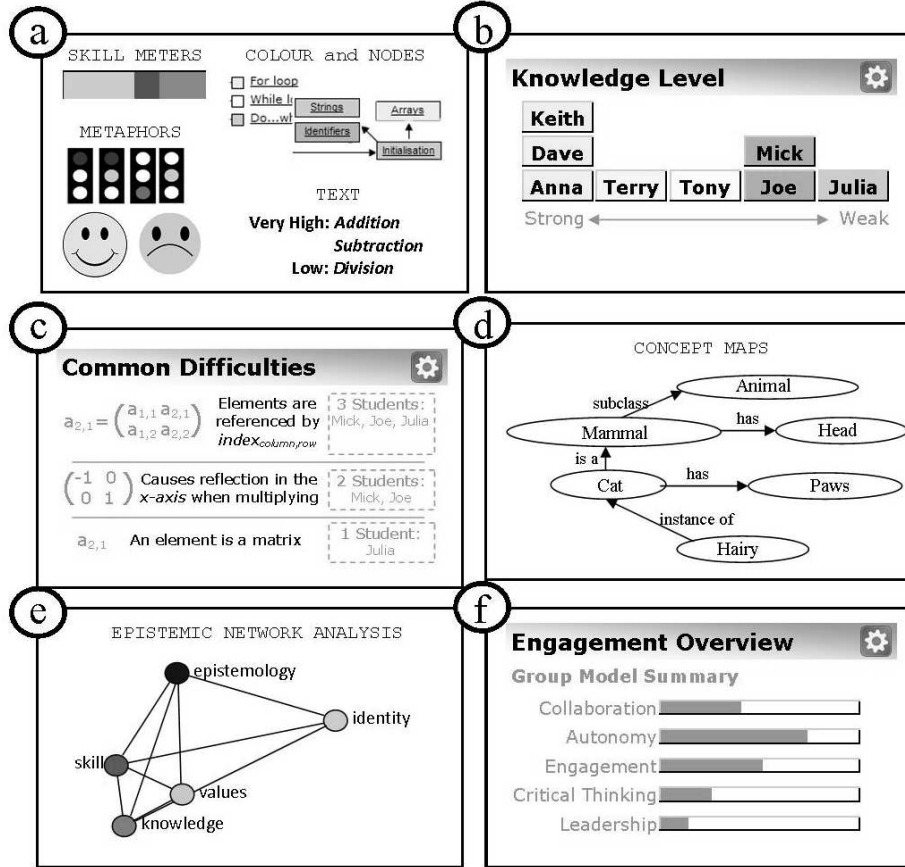
**Abstract.** Information on epistemic beliefs has the potential to enrich feedback to students and teachers, through open learner modelling (OLM). We outline existing OLM applications with epistemic content and ways in which more holistic aspects of learning and development (epistemic beliefs, values, identity cognition etc.) may extend OLM for 21<sup>st</sup> Century learning. We propose three steps to extend epistemic network analysis to provide an OLM which contains epistemic beliefs.

**Keywords:** Open Learner Modelling. Epistemic Beliefs.

## 1 Introduction

In adaptive learning environments (ALEs), a learner model (LM) represents student knowledge, allowing for personalisation and adaptation towards learners and their current needs [1]. Traditionally the information in the LM may be read only by the ALE (i.e. it is *closed* to the learner it represents.) An *open* learner model (OLM) allows learner access to the LM's content in a meaningful way, for example through a visual representation of its content, during interaction. OLMs may be presented in a variety of forms from skill meters and coloured nodes (Fig 1, a,b), through to concept maps (Fig 1, d), animations and domain specific representations (Fig 1, c) [2]. Learner responsibility, awareness and independence in learning are benefits of viewing an OLM, and metacognitive activities such as self-assessment, planning and reflection may be promoted [2,3,4].

Traditionally the content of the LM may range from core competencies (knowledge, misconceptions etc. [5]) to measures of affect (e.g. motivation [3]). Information less commonly modelled includes epistemic activities such as argument construction [6]. Such activities are highly relevant to learning and may potentially enrich the learning-based feedback OLMs provide. In this paper we look at the suitability of including epistemic beliefs in OLMs, and consider methods to capture and display epistemic information in the OLM context and conclude with a method for doing this.



**Fig. 1.** Example methods for presenting OLM information. The top two rows show existing ways of presenting the information through: (a) knowledge level skill meters, metaphors coloured nodes and text etc.; (b) group model information; (c) detailed or domain specific presentations; (d) concept maps. The bottom row shows potential ways further epistemic information may be presented using existing means: (e) epistemic network analysis (adapted from [11]); (f) overviews of 21<sup>st</sup> Century skill mastery.

## 2 Epistemic Beliefs in the Context of Open Learner Models

Learning is not restricted to mastering concepts, procedures or specific skills, but includes the “*ability to think, act and interact with others in productive ways to solve complex tasks*” [7]. Epistemic beliefs help address this point and can be considered as those an individual holds about the nature of knowledge, and ‘knowing information’. Epistemic beliefs focus on the systematic linking of knowledge and the justification of understanding using evidence or prior understanding [8].

In the case of the epistemic activity of *argument construction* this can be summarised formally by Toulmin’s [9] argumentation structure. OLMs such as xOLM [3]

use this structure to formally reason about student understanding, although these beliefs belong to the system rather than being the epistemic beliefs of the student. The OLM presentation is highly visual, presents links between evidence and makes predictions about student ability. Warrants that justify claims are important to establish their legitimacy. OLMs such as STyLE-OLM [5] allow joint construction of the LM, requiring learners to justify beliefs, and in doing so the OLM may foster reflective thinking in students, through negotiation. Again, representations are highly visual and links are forged between beliefs. Relationships modelled are epistemic in nature and show the systematic linking of low-level information. This is similar in concept mapping. In Flexi-OLM [4] learners constructed their own OLM presentations by linking concepts. Relationships specified included formal relationships, information related to planning learning, and information to aid future knowledge acquisition. In such activities, labels on links between information are important for developing epistemological understanding. These examples show that existing OLMs have the potential to capture and model epistemic information. Future challenges include scaling up the domain content, increasing the epistemic information quality, visualising greater volumes of epistemic beliefs, and inferring epistemic beliefs not explicitly stated by the learner.

Stoeger [10] highlights the potential for creating a LM composed of epistemic beliefs and proposes a non-computer based learner model, constructed from fixed questionnaire items (e.g. “The manner in which I learn [maths] will never change”). Using the model, composed of three principal facets (epistemic inclination, epistemic acquisition and knowledge characteristics), he demonstrates epistemic beliefs are effective predictors of ability and more accurate than IQ tests. Extending OLMs to include these facets provides a starting point for more formally modelling epistemic beliefs.

In the context of 21<sup>st</sup> Century learning, epistemic beliefs may not be solely about knowledge and its acquisition, but of wider social/cultural experience, values and practices [7] – potentially, a community of practice. For example, epistemic games encourage learners to use concepts/ procedures in activities to learn what it is to *think* and *act* as a member of a specific profession (e.g., journalist) [7]. The professional competence is modelled as an epistemic frame containing inter-related *skills*, *knowledge*, *identity conceptions*, *values* and *epistemological beliefs* [11]. The classroom/home setting constitutes itself a community of practice, albeit a ‘non-professionally based’ one; arguably OLMs could also model student identity conceptions, values and epistemic beliefs – by being extended to encompass rich, contextual ‘epistemic frame’ inferences. Epistemic network analysis (ENA) [11] is used to model and display epistemic frame information, and the extent to which students internalise its attributes. Using graphs and network diagrams the model is visualised (in ways similar to Fig 1e), and changes over time may be discerned. OLMs could be extended to include ENA-type information, and so give feedback to students and teachers in real time regarding how they resemble epistemic frames of experienced members of the community of practice. The LM incorporates process and product data, and the OLM reveals this information to the student. This makes explicit, normally tacit metacognitive processes that experts participate in to engage students in 21<sup>st</sup> century learning. In alignment with the initial aims of OLMs, this may help with short and long term planning, in addition to being a source to promote reflection. This extends the benefits of OLMs to permit the acquisition of 21<sup>st</sup> Century skills (e.g. collaboration [6], leadership [7], critical thinking [11]), through inspection of episte-

mologically based information. These skills, often labelled “soft skills”, are recognised as key to innovation. They make the process of knowledge building accessible to all, permitting the development of new ideas that are of value to others in a community. Students can build knowledge relative to their current level of understanding through acculturation to the wider social/cultural practices of a community and experience more meaningful learning.

Thus: existing OLMs have the potential to encompass epistemic information within current technologies; techniques exist as a starting point for modelling learners’ epistemic beliefs; and through considering the wider context provided by an epistemic frame, OLMs can be extended to support the acquisition of 21<sup>st</sup> Century skills.

### 3 Realising Epistemic Open Learner Model Content

Epistemic information may typically originate from two sources: *process data* (people interaction, whether between learners, a teacher or a non-learner) and *product data* (tangible outcomes/artefacts, e.g. from learning activities) [7]. For OLMs, epistemic beliefs could explicitly result from educational activities (e.g. writing reflective prose [11], concept mapping [4] or negotiation [5]), or OLMs may be extended to encompass other, more informal, sources (e.g. teacher observation, chat logs etc.). It is important to acknowledge that epistemic information may be latent and affected by other measurable attributes [7] as a result of learners systematically linking information [11], and that strong relations exist between epistemological facets. Information is often modelled to a course level of granularity for precisely this reason [11].

OLM based epistemic information, originating in the classroom or home, has practical benefits for students, teachers and parents alike. Independent from technology, teachers and parents can use the information to scaffold students’ learning and further 21<sup>st</sup> Century skills that mainstream classroom technologies do not necessarily promote. Teachers and parents may draw on their own personal experience to support students in developing aspects of these skills, using the epistemic OLM information. Furthermore, teachers’ feedback to students often draws on in-depth knowledge of local circumstances and general context [13]. Epistemic OLM information could specify the context in which to interpret core abilities (knowledge, misconceptions etc.) and visualise pedagogically-based information. This may allow the prediction of future behaviour, its evolution over time and inter-student relationships or belief networks that exist; these are useful tools for designing educational interaction.

Our research project makes advances in three steps to realise the vision that OLMs for 21<sup>st</sup> Century learning may include more holistic aspects of learning and development. These include epistemic beliefs, values, and identity cognitions, in addition to ‘classic’ KSAs (knowledge, skills and aptitudes).

The first step is towards automating ENA [11], which has so far been realised by employing human coders. The construction of the basic data table, required to analyse inter-frame development, will be automated by graph-theoretical means: the list of time slices together with the frequencies of frame elements. In our approach we will apply natural language processing techniques to extract concepts, relationships and sentiments, and will use machine learning techniques to build classifiers (e.g. Support Vector Machines). These techniques rely heavily on corpus data that is obtained when

human ‘raters’ perform content analysis in order to code student-produced materials (mainly students’ writing documents) in terms of the epistemic frame dimensions. This content analysis (valuable in its own right to answer research questions) will then yield the data required to train the automatic classification method.

In the second step we will automate the analysis of the adjacency matrices that can be built from the basic data table. This will require respective software to be written and/or to reuse existing implementations of graph algorithms, such as the ones used for social network analysis.

Our third step will visualise the information contained in adjacency matrices as well as plotting graph theoretical parameters (such as centrality, density, etc.) over time. In addition to writing the respective software, this requires research into the graphical interface provided to the users. As stated above, existing OLM presentations containing epistemic information are highly visual (links between information, coloured nodes etc.) and network diagrams/graphs are appropriate methods for representing epistemic information, with an emphasis on clarity. This is our starting point for visualisation, and the OLM may be extended to include more emerging techniques (e.g. tag clouds, timelines or sparklines [12]), which also allow collaborative activity content to be represented.

In summary: appropriate information sources exist to build on the capabilities of OLMs highlighted in Section 2, and extend epistemic information in alignment with current student and teacher practices; secondly, we have highlighted that epistemic OLM information may have the potential to support human-based scaffolding of students’ 21<sup>st</sup> Century skill development; finally, we have outlined three steps towards an OLM for 21<sup>st</sup> Century learning that can include more holistic aspects of learning development.

## 4 Summary

Existing OLMs include activities that are appropriate to formally model epistemic beliefs. By capturing aspects of process (people interaction) and product (learning artefact) data, epistemic OLM information may be modelled and presented in a highly visual manner. This has the potential to extend the state-of-the art to allow OLMs to support students, teachers and parents in their respective roles, and to further students’ development of epistemic practices and 21<sup>st</sup> Century skills (e.g. collaboration, critical thinking). In our work, we will extend approaches developed in former OLM research to model and visualise epistemic activities and beliefs, and we will extend ENA in three steps so that it can be applied to the assessment of school-relevant 21<sup>st</sup> century learning.

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# Understanding Student Attention to Adaptive Hints with Eye-Tracking

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**Abstract.** Prime Climb is an educational game that provides individualized support for learning number factorization skills. This support is delivered by a pedagogical agent in the form of hints based on a model of student learning. Previous studies with Prime Climb indicated that students may not always be paying attentions to the hints, even when they are justified. In this paper we discuss preliminary work on using eye tracking data on user attention patterns to better understand if and how students process the agent’s personalized hints, with the long term goal of making hint delivery more effective.

**Keywords:** Adaptive help, educational games, pedagogical agents, eye-tracking

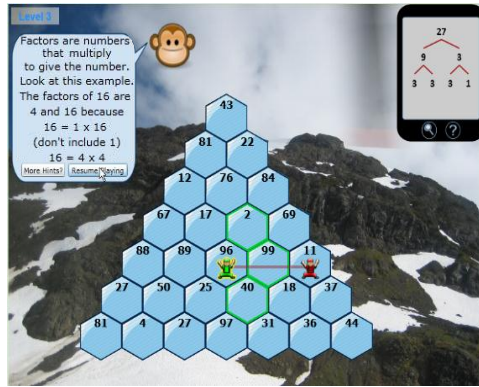
## 1 Introduction

Educational games (edu-games) are one of the most promising media for the development of innovative computer-based pedagogy, however, while there is ample evidence that edu-games are highly engaging, there is less direct support for evidentiary claims about what is learned through play [e.g. 1, 2]. We believe that edu-games effectiveness can be improved by making them more adaptive to the specific needs of individual students, and we are doing so by devising intelligent pedagogical agents that can provide individualized support to student learning during game playing [3]. Providing this support is challenging because it requires a trade-off between fostering learning and maintaining engagement. Our long-term goal is to enable our agents to achieve this trade-off by relying on models of both student learning and affect [3]. In this paper, we focus on an issue that has been raised in the context of various user-adaptive learning environments: are interactive, personalized didactic hints effective? Do students pay attention to them [e.g. 11]? We investigate this issue in relation to the user-adaptive hints provided by the pedagogical agent in Prime Climb, an edu-game for number factorization. The current agent’s version provides hints based on a model of student learning [3]. A previous study showed that the adaptive version of Prime Climb did not perform better than a version with random hints, and provided initial indications that one reason for this outcome is student limited attention to the agent’s adaptive hints. In that study, attention was estimated from how long students had the hints open on the screen. In this paper, we start looking at a more accurate measure of attention, based on eye-tracking data. We

present preliminary results from the analysis of one student’s interaction with Prime Climb, as a proof of concept for this methodology.

User-adaptive educational games are receiving increasing attention [e.g. 4, 5] although most of the existing work has not been formally evaluated in terms of how adaptive game components contribute to learning. There has also been increasing interest in using eye-tracking to gain insights on the cognitive and perceptual processes underlying a user’s performance with an interactive system [6, 11]. In this paper, we contribute to this line of research by using gaze information to understand if/how users attend to a system’s adaptive interventions. Adaptive incremental hints are commonly used in personalized learning environments, but their effectiveness is in question because there are students who ignore them, or use them to extract quick solutions from the system [8, 11]. Researchers have proposed predictive models of hint processing based on reaction-time (lapsed time between the hint being displayed and the next observable student action) [8, 9]. Despite encouraging results, these models cannot capture the details of the student’s cognitive reactions to a hint because these are unobservable when using only reaction time. We investigate how to uncover these details by relying on attention patterns captured via eye-tracking. In the rest of the paper, we first describe the Prime Climb edu-game and its personalized agent. We then provide an example of attention analysis and the insights that it can provide.

## 2 The Prime Climb Game



**Figure 1: The Prime Climb interface.**

individualized support, both on demand and unsolicited, when the student does not seem to be learning from the game. To provide appropriate interventions, the agent must understand when incorrect moves are due to a lack of factorization knowledge vs. distraction errors, and when good moves reflect knowledge vs. lucky guesses. Thus, Prime Climb includes a probabilistic student model that assesses the student’s factorization skills for each number involved in game playing, based on the student’s game actions [3]. The agent gives hints at incremental levels of detail, if the student

In Prime Climb, students in 6<sup>th</sup> and 7<sup>th</sup> grade practice number factorization by pairing up to climb a series of mountains. Each mountain is divided into numbered sectors (see Figure 1), and players must move to numbers that do not share common factors with their partner’s number, otherwise they fall. To help students, Prime Climb includes the Magnifying Glass, a tool that allows players to view the factorization for any number on a mountain in the device at the top-right corner of the interface (see Figure 1). Each student also has a pedagogical agent (Figure 1) that provides

model predicts that the student doesn't know how to factorize one of the numbers involved in the current move (regardless of move correctness). The agent starts by reminding the student to evaluate her move in term of number factorization, then it generates a *tool* hint that encourages the student to use the magnifying glass to see relevant factorizations. If the student needs further help, the agent gives *definition* hints designed to re-teach what is a factor via explanations and generic examples. There are two different factorization definitions ("Factors are numbers that divide evenly into the number", "Factors are numbers that multiply to give the number"). The agent alternates which definition to give first, and gives the second the next time it needs to provide a hint. The generic examples that accompany the definitions change for every hint. Finally, the agent provides a *bottom-out* hint giving the factorization of the two numbers involved in the current move. Students can choose to progress through the various levels by asking. Otherwise, the agent goes through the progression as the student model calls for a new hint. A hint is displayed until the student selects to resume playing or to access the next hint level, if available.

### 3 Sample gaze analysis

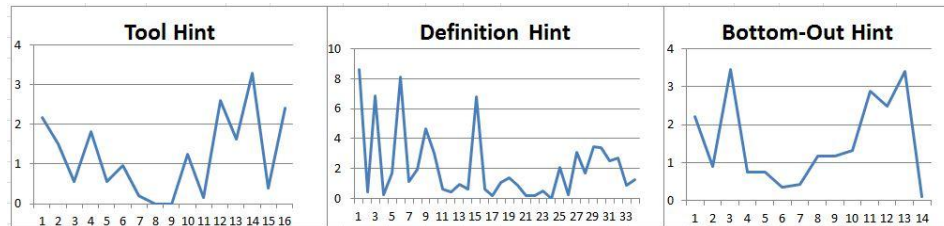
Previous studies with Prime Climb suggested that students may often ignore agent's hints, even when these hints are well justified (i.e. based on a reliable student model's assessment) [3]. Those results were based on hint *display time* (duration of time a hint stays open on the screen) as a rough indication of attention. However, display time can be unreliable because students may not attend a displayed hint, or be fast readers and thus processing a hint even when display time seems short. For a more precise analysis, we are using a Tobii T120 eye-tracker to capture students' attention patterns. At the time of writing we have reliable data for only one subject, which we present as an example of the type of analysis that eye-tracking can support.

**Table 1: Summary of statistics on fixation time and display time for each hint type**

	Tool hint	Definition Hint	Bottom-Out Hint
Number of hints	16	34	15
Fixation Time Mean (st dev)	1.22 (0.99)	2.14 (2.31)	1.53 (1.1)

The agent's adaptive hints can be divided into two categories: *short hints*, which are on average 8 words long and include tool or *bottom-out* hints; *long hints*, which are on average 25 words long and include all *definition* hints. The amount of time it would take an average-speed reader to read the text would be 2.3 seconds and 7.3 seconds for the *short* and *long* hint respectively. Table 1 shows mean and standard deviation of total fixation time (i.e. total time a student's gaze rested on a displayed hint) for each hint type. These numbers show that, although this particular student spent more time looking at the longer hints (*definition* hints), the increase is not proportional to the increased hint length, and in fact there is no statistically significant difference between the reading time for these three hint types (as tested via ANOVA). Furthermore, fixation time is much shorter than the time an average-reader would need to read the hints. The high standard deviation on all three measures indicates a

trend of selective attention. Figure 2 visualizes this trend by showing total fixation time on each individual hint, for each hint category. The x-axes show hint number in each category.



**Figure 2: Total fixation time for each displayed hint**

It is interesting to see that, for about the first half of the displayed *definition* hints, there is a pattern of attention being high for one hint, and low for the *definition* hint given as the next step in the hinting cycle. This pattern suggests that this student tends to ignore the second *definition* hint, possibly because two subsequent *definition* hints are perceived as redundant. Student attention then decreases substantially for all of the second half of *definition* hints provided. In contrast, attention to *tool* and *bottom-out* hints reaches its low in the middle of the interaction, but picks up again towards the end. A possible explanation for these trends is that *definition* hints become less useful overtime, as mountains get more difficult (i.e. include larger numbers), because the student is already familiar with the factorization definitions and the generic examples in the hint don't help directly with the current moves. However, apparently the student still needs help dealing with the higher numbers, so she does read *short* hints when they appear and specifically attends to *bottom-out* hints because they provide the information needed to understand the outcome of the current move. We need of course to collect more data before drawing any firm conclusion. These trends, however, are consistent with previous indications that attention to some the Prime Climb hints can be scarce and start providing specific information on why and how the current hinting strategy needs to be revised to make it more effective. Further insights can be derived from a more detailed analysis of the attention patterns associated with specific hints, e.g. attention shifts between a hint and relevant places of the mountain (or lack thereof). Following the approaches proposed in [4] and [10], we plan to apply data mining techniques to discover patterns associated with learning/reasoning vs. confusion or distraction. In the long term, we want to use this information to add to the Prime Climb user model a classifier that can recognize these patterns in real time, and use the information to generate adaptive interventions geared at focusing student attention when needed.

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# Improving Searching and Browsing Capabilities of Learning Object Repositories

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**Abstract.** Learning object repositories are a basic piece of virtual learning environments used for content management. Nevertheless, learning objects have special characteristics that make traditional solutions for content management ineffective. In particular, browsing and searching for learning objects cannot be based on the typical authoritative metadata used for describing content, such as author, title or publication date, among others. We propose to build a social layer on top of a learning object repository, providing final users with additional services for describing, rating and curating learning objects from a teaching perspective. All these interactions among users, services and resources can be captured and further analyzed, so both browsing and searching can be personalized according to user profile and the educational context, helping users to find the most valuable resources for their learning process. In this paper we propose to use reputation schemes and collaborative filtering techniques for improving the user interface of a DSpace based learning object repository.

**Keywords:** Learning Object Repositories, Browsing, Searching, Recommendation Systems, Collaborative Filtering, DSpace, Metadata, Paradata

## 1 Introduction

Since the introduction of Information and Communication Technologies in the field of education, almost every educational institution has adopted an e-learning solution, although with different approaches. Virtual learning environments are one of the most common tools used to implement an e-learning platform, typically including a module for content management. Usually, content is understood as complete courses, but the reality is that learning resources can be very different according to their type, format and granularity [2].

In order to encourage its usage, the most important issue for a learning object repository integrated in a virtual learning environment is being able to build a true social learning network around it, promoting the creation, sharing

and reuse of learning resources among the members of the learning community, mainly both learners and teachers. This can be only done if the learning object repository, regardless of its technology, provides its users with a virtual learning environment and a true learning experience. These learning experiences can be used in order to get knowledge about the needs of learners, their preferences in the use of learning objects and to identify learning objects in the repository that are less attractive to them. All this information can be used in order to improve the repository by updating the descriptions of learning objects according to what we learnt (making the appropriate learning object easier to find through additional metadata [3]), improving the services of the repository itself (making it easier to use) and improving the quality of the institutional repository by deleting or improving the irrelevant resources and promoting the more useful ones. The learning object repository is an important element of the virtual learning environment but it is not the only one and, of course, learners may search for resources outside the institutional "walled garden", mainly through Google and other search engines. Nevertheless, the main problem for learners is to filter among the thousands of results returned by a general purpose search engine. We encourage our learners to use the institutional repository as part of their learning process.

This paper is organized as follows: Section 2 describes the use of learning object repositories as an important tool for supporting both learners and teachers. Section 3 describes the functionalities of an ideal learning object repository which uses a social layer on top of it to improve searching and browsing capabilities. Finally, Section 4 outlines the main advantages of the proposed system, the implementation issues and the current and future research topics of this project.

## 2 Learning Object Repositories

Learning objects are stored in learning object repositories, which can be considered a specific kind of content management system for educational resources but much more versatile [7]. Although, as stated before, traditional CMS tools can be used to store, describe and share learning objects (such as Drupal or OpenCMS, among many other open source software tools), these tools are usually oriented towards web content. According to [5], repositories are differentiated from other digital collections because the content is deposited in the repository together with its metadata; and such content is accessible through a basic set of services (i.e. put, get, search, etc.). Depending on the specific needs of the community using the repository, this will provide additional tailored services, but all repositories should at least provide two basic ones: content preservation and content reusing [1].

Obviously, digital repositories are a way to organize learning objects (and their parts that can be processed separately) in collections, although there are several specific issues that must be firstly addressed. For example, an exercise (which is basically a text defining a problem and, optionally, its solution, another text which may include references to the use of software or tables with data, for

instance) is a typical learning object. But, differently to classical items in a collection of a digital repository, exercises may have neither a title nor even an author, the two main fields used for finding a book. Other typical learning objects can be data sets, mathematical proofs, equations, simulations, and so. Usually, learners search through these kinds of resources not by title or author, but by keyword or, even better, using a hierarchical taxonomy specially designed. Therefore, it becomes necessary to rethink the traditional way of describing learning resources, using criteria related to the learning process but maintaining a minimum description for archiving purposes. Learning object repositories should be designed for final users, that is, learners and teachers [4], promoting content reutilization rather than preservation. Both concepts (preservation and reutilization) are somehow contradictory (institutional, top-down vs social, bottom-up) but a tradeoff can be achieved by combining digital repositories with web 2.0 services.

## 2.1 DSpace as a learning object repository

DSpace<sup>1</sup> is an open source platform developed by MIT and Hewlett-Packard in 2002 for creating digital repositories, as initially outlined in [8]. DSpace preserves and enables easy and open access to all types of digital content including text, images, moving images, mpegs and data sets. It is used by more than one thousand institutions and it has a large community of developers, becoming a *de facto* standard for building open repositories.

DSpace organizes resources in a hierarchical structure based on communities (and, recursively, subcommunities) and, finally, collections. These contain the items (i.e. the resources) which are described using a metadata profile, usually non qualified Dublin Core. With the default DSpace user interface, users can search and browse by author, title, publication date and keywords, as well as through the hierarchical structure of communities and collections. But, according to their nature, some learning objects may have or not title, author, creation date, etc., so they cannot be accessed by classical retrieval mechanisms used in digital libraries or repositories. In fact, DSpace has to be customized to change the basic fields used for searching and browsing, as well as all the workflows related to the process of adding new resources to the repository. From a teaching perspective, learners should retrieve resources not from a list of search results but within a specific educational context. DSpace (as any other large collection of resources) suffers from the "Google effect", that is, a search based on a simple keyword such as "Statistics" may return thousands of resources, which is not a good result from a teaching perspective<sup>2</sup>. It is well known that most users click on the first three results (up to 62.53%, see <sup>3</sup>), so it is very important to determine a proper ranking of learning resources, providing learners with the most appropriate content according to their profile and context.

<sup>1</sup> <http://www.dspace.org/>

<sup>2</sup> See <http://dspace-dev.dsi.uminho.pt> as an example of recommender system.

<sup>3</sup> <http://www.webuildpages.com/jim/click-rate-for-top-10-search-results/>

### 3 Improving browsing and searching

As described in [6], our goal is to provide a layer of web 2.0 services on top of each learning object stored in the repository. These services include adding comments to a learning object, rating it, starring it as a favorite resource, tagging it, sharing it through different social networks and, finally, subscribing to it in order to be aware of all the activity generated around such learning object. All the information generated during the interaction between users, services and resources is stored in each learning object and/or user profile, if available. All this information is known as paradata<sup>4</sup>, and it can be used for our adaptation purposes in two different ways: supporting users when browsing and searching (i.e. filtering before finding) and sorting results (i.e. filtering after finding). In our case, paradata is composed of 5-tuples  $\{U, S, R, X, T\}$  meaning that user  $U$  used service  $S$  on resource  $R$  with result  $X$  in moment  $T$ . By means of data mining techniques, these data can be analyzed and reintroduced into the system to enhance browsing and searching capabilities.

#### 3.1 Possible uses of paradata

For each resource, we know the following: the number of times it has been accessed, the number of times it has been downloaded, the number of comments placed on it, the number and average of ratings, the number of times it has been favorited, the number of times it has been shared and the number of users subscribed to it.

On the other hand, for each user, we know the following according to its role (manager, teacher, learner or anonymous visitor). For teachers, we are interested in knowing the list of subjects she is in charge of, as her activity on resources related to those subjects will have an important weight. For learners, we know the list of subjects she is/has been enrolled in, the languages she is competent (and her preferred one), previous and current professional experience (if available) as well as all the repository services used in a period of time. Although it is out of the scope of this paper, all this information could be available by means of specifications like IMS Learner Information Profile, in order to promote interoperability with other e-learning systems.

Once the layer of services is available to all users and the proposed system has been gathering interaction data during an adequate period of time (i.e. an academic semester), it is possible to use such data for computing the heuristics that will be used by the reputation scheme to rank both users and resources, providing useful information about:

- The most popular resource: popularity can be both rank based or activity based, or any combination of both. Not only the most popular resources are interesting, the worst ranked ones need to be analyzed by teachers in order to detect potential problems. On the other hand, it might be useful to identify

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<sup>4</sup> <http://nsdlnetwork.org/stemexchange/paradata>

unused resources. This may lead to detecting wrong metadata descriptions which may cause a resource to be non findable.

- The most active users: analogously, users can be ranked according to their level of activity. In a virtual learning environment, where peer-to-peer learning is promoted as part of the underlying pedagogical model, learners can build a reputation by creating, sharing and answering other peers' questions, all these actions rated by the other users. On the other hand, teachers can act as peer experts in one or more subjects.
- The most common tags used for describing resources: although resources have been already described by both librarians and teachers according to several taxonomies (domain specific keywords, resource type, etc.), users can add their own tags for describing resources as in delicious. These tags can be analyzed and further incorporated into metadata as new keywords, for example.
- Relationships between resources: like Amazon, collaborative filtering can be used to detect which resources can be potentially more interesting according to the implicit navigational behavior of users with similar profiles. This information will be used to determine the most adequate resources related to a given one.

### 3.2 Improving the user experience

When a user reaches the DSpace repository, there is usually a list of the most recently added resources. We propose to replace the items in this list with the most adequate ones according to her profile (i.e. the most relevant ones with respect to the subjects she is enrolled in). A second list with the resources previously used and/or the most popular is also desirable.

On the other hand, when the same user performs a search and obtains a list of results, we propose to modify two different aspects. Firstly, only a few results are shown (i.e. five to ten), the most important ones according to the underlying reputation scheme which uses both user profile and the available paradata. Secondly, the resources most related to these search results are also shown, promoting a browsing strategy through a local network of resources, updating it according to user's navigational behavior. From a teacher's perspective, this is better than providing learners with hundreds of resources without any contextual support.

## 4 Discussion

Learning object repositories are a very important piece of any e-learning platform, although they are currently being underused by final users, specially learners. In order to promote repository usage, we propose to add a layer of web 2.0 services on top of the repository, bridging resources to the learning process. The interactions between users, services and resources generate a lot of paradata that

may be captured and further analyzed for personalization purposes. Both searching and browsing can be adapted to user's profile, improving her experience when using the repository.

Nevertheless, there are some well known issues that must be faced regarding to the way learning resources must be described. It is not easy to establish a taxonomy for describing all the resources in an institutional repository. Due to the variety of contents, such a taxonomy would have probably too many levels, making it too complex for most users. On the other hand, learning activities that promote the use of the repository must be also designed, in order to encourage learners to adopt a more active role in their learning process.

This work is part of a three year research project (2011-2013) on analyzing usage of repositories and social networks in virtual learning environments. Currently now we are modifying our DSpace institutional repository<sup>5</sup> in order to include the layer of services as well as the mechanisms for paradata gathering. We expect that in Fall 2011 we will be able to deploy a first version of the repository and start capturing users' interactions. Current and future research lines around this topic include the creation of reputation schemes for both users and resources, using explicit and implicit paradata. Making repository services available from social networks (where students are) is also an interesting possibility.

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<sup>5</sup> <http://openaccess.uoc.edu/webapps/o2/?locale=en>

# Identifying Requirements for a Psycho-Pedagogical Mash-up Design for Personalising the Learning Environment

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**Abstract.** This paper examines educational components that influence the creation of mash-up designs in a Personalised Learning Environment (PLE). These educational components are linking widgets, small tools, to psycho-pedagogical information and competences of a learner. Taking these into account principles and rules for an adequate PLE mash-up can be identified and empirically studied. Finally an approach is introduced to validate these assumptions.

**Keywords:** mash-up design, self-regulated learning, personal learning environments.

## 1 Introduction

In the context of e-learning Personalised Learning Environments (PLEs) attract more and more users. PLEs are environments that combine services and tools, and therefore, provide access to different learning resources on the web. By means of this functionality, a learner is enabled to control, manage and compose her own learning environment, which could be maintained across institutions (e.g. from school through university and to a workplace).

However, it seems to be unclear what psycho-pedagogical rules should be applied to mash up a PLE. Therefore, the main purpose of this paper is to identify important educational components that have an influence on composing a PLE during a self-regulated learning (SRL) process. These educational components will be the basis for adequate recommendations for mashing up a PLE. The usefulness of the educational components will be empirically studied. For this reason a validation approach is introduced.

## **2 Educational components**

In the EC-funded project ROLE (Responsive Open Learning Environment) the SRL behaviour of a learner within a PLE is based on a SRL process model. The model consists of four phases (see section 2.1). An important building block for mashing-up a PLE and modelling SRL is the categorisation of learning strategy strategies. In order to apply learning strategies, learning techniques are used. Learning techniques can be applied by using widgets or tools. In this way tools can be related to learning strategies. Further building blocks are competences, such as tool competences, SRL competences.

For compiling the widgets rules and principles need to be taken into account. First, the mash-up is defined and explained on the level of learning strategies. Meaningful designs can be derived through the assignment of learning tools to learning techniques and strategies. Secondly, the tool and SRL competences of learners are considered, e.g. if learners are able to use the mash-up. Though the relation of these competences to learners, the mash-up can be related to learners and his/her PLE profile (this is part of the SRL process model).

### **2.1 The self-regulated learning process model**

The SRL process model in ROLE generally builds upon the cyclic SRL model introduced by [9], also see [3]. [9] proposed three SRL phases: the forethought phase, the performance phase and the self-reflection phase. In ROLE it was assumed that the learner will implicitly or explicitly perform four phases based on four predominant activity groups. These phases are: (1) learner profile information is defined or revised, (2) learner finds and selects learning resources, (3) learner works on selected resources, and (4) learner reflects and reacts on learning strategies, achievements and usefulness [3].

Within this SRL process the learners perform key activities, such as goal setting, self-monitoring, self-evaluation, help seeking, time planning and management. These key activities are of metacognitive nature and enable the learners to take control over their own learning processes and influence the actual learning and working phase (3). The ROLE SRL process model features the possibility to repeat the complete learning cycle for every learning task and recursiveness, which can be understood as possible iteration of every activity or set of activities within the learning cycle. In general, the SRL process model can be seen as repository of learning strategies and techniques to carry out learning activities (e.g. Learning Event Activities [8]).

### **2.2 Assigning learning techniques to learning strategies**

From a psycho-pedagogical point of view, it seems suitable to argue that learning within a configurable PLE is subject to certain learning conditions. In this regard, learning strategies and learning techniques play a crucial role. It is suggested [4] that applying appropriate learning strategies and using learning techniques in the right manner lead to better learning outcomes. Surprisingly, literature provides no clear

distinction between learning strategies and learning techniques e.g. [6], [1]. However, learning strategy is rather an umbrella term to classify learning techniques. Learning techniques in turn are highly sophisticated methods to fulfil or act out learning activities. Learning strategies are the “What” (What do I want to do?: organize, manage time, plan etc.) and learning techniques refer to the “How” (How do I organize?: e.g. Mind-map, slow-fast, calendar etc.).

According to the classification of strategies [7] organization strategies, elaboration strategies, and rehearsal strategies are assigned as cognitive strategies, whereas self-control is considered as a metacognitive strategy and time management as resource management. For each type of learning strategy different learning techniques are available.

### **2.3 Assigning widgets to learning techniques**

The classification of learning techniques to learning strategies introduced above provides the basis of matching learning techniques to widgets. Widgets are small programs that usually fulfil one task that are used in PLEs. One application for such widgets could be a language learning scenario [5]. In an English learning context a voice-recording widget can be used to hear one’s pronunciation of words and compare it to recordings of peers or pronunciation examples provided by online English dictionary services.

In reference to a learning strategy, the voice-recording widget imputes meta-cognitive strategies, more precisely, regulation and evaluation. Therefore, the voice recording widget could be assigned to the actual learning technique recording.

However, why should widgets be assigned to corresponding learning techniques? If widgets are assigned to learning techniques, ROLE services could provide recommendations according to appropriate learning strategies and learning techniques, respectively, based on scientific research. The use of learning strategies and techniques improve learning outcome and success, especially in the context of self-regulated learning [9].

### **2.4 The role of competences**

Once widgets are classified another education component comes to play, the competence. In ROLE the focus lays mainly on tool and SRL competences. The tool competence is captured through the usage statistics and user input (assessment) and influences the order in which the tools are recommended. The competence model in ROLE distincts between domain knowledge, skills and competences and corresponds with the European qualification framework model [2].

Further on, the term competence is used as a master category. Special competence areas are domain competences, tool competences, and SRL competences. In order to learn effectively and efficiently in a self-regulated way within a PLE, the learner needs competences particularly on the SRL and tool levels. On the SRL side, the environmental structuring competence, which can be seen as a competence in coping with a learning environment in terms of assembling the widgets and managing

resources, is crucial. Tool competence comprises the ability to perform learning activities with a specific tool, it captures declarative knowledge (learning tool) and procedural knowledge (learning activity).

### **3 Mash-up design**

The identified education components come into play by means of composing an applicable mash-up as a teacher or to recommend a mash-up design by the ROLE system that does not overtax or distract the learner [comp. 5]. For instance, a learner sets the learning goal to learn new vocabulary and pronounce the words accurately in in the first phase of the SRL process model. In this language learning scenario ROLE services identify the need for regulation, a metacognitive strategy, respectively (What should be done?). Additionally, the competences that are required to accomplish this learning goal (according to the ROLE competence model) are assessed. These enable ROLE services to recommend e.g. a voice-recording-widget (“How should it be done?”), which should be added to the ROLE mash-up design in the second phase of the SRL process model. In the third phase the learner actually uses the widget. The next step is the crucial one: There are other widgets available that could benefit the learner, such as the text2speech or a dictionary-tool.

However, it has to be clarified, whether these other widgets distract or confuse the learner and/or what number of widgets would be suitable for this particular learning attempt. Further research questions arise: Is the learning outcome higher if planning or goal-setting- (metacognitive), concrete learning- (cognitive) and feedback-widgets (meta-cognitive) are mash-up within one single design or should they be separated? A validation approach will attempt to bridge that gap.

### **4 Validation and evaluation criteria**

As outlined above, systematic investigations of the moderating, and especially interacting effects of administering different widgets in a PLE mash-up are lacking. The present three step validation approach is designed to fill the lacuna.

In the first step it is planned to empirically verify the assignment of learning techniques to learning strategies. For this purpose a list of learning strategies and a list of learning techniques will be presented to experts of the research field, who then are kindly asked to assort the learning techniques to associated learning strategies. An interrater-reliability analysis will be applied. In the second step the learning techniques are supposed to be associated with corresponding widgets. Again, expert of the research field will be asked to assign widgets to learning techniques.

Hence, appropriate learning strategies and learning techniques need to be identified for a concrete language learning scenario. This psycho-pedagogical information will be implemented in the ROLE services according to the SRL process model and by taking into account the competences, described by the competence model. In the third validation step an experimental pre-post 3x2 design will be determined. Independent variables are mash-up design operationalized by the number

of widgets administered at the first use (0 vs. 3 vs. 6) and the pre-set degree of freedom operationalized dichotomous (maximum guidance vs. maximum freedom). During the learning phase the learning should be allowed to personalise the mash-up. In a pre-phase of the experiment a language test will be applied. In a post-phase of the experiment a parallel version of this language test will be applied, and the difference between these two tests will be interpreted as the learning outcome. As an additional performance indicator grades provided by lecturers in a university context might be feasible. Furthermore, log- and CAM (Contextual Metadata Model) data, respectively, will be analysed.

## 4 Conclusion and Outlook

To sum up, assigning widgets to psycho-pedagogical information has been identified to be an important issue to provide learners with meaningful recommendation in order to guide them through the SRL process. In this regard, Tool and SRL competences need to be taken into account to meet the requirement of a PLE. Validation and evaluation of the moderating, and interacting effects of these education components on an empirical level will be the focus of the further research activities.

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## **TOWARDS USER MODELING AND ADAPTIVE SYSTEMS FOR ALL (TUMAS-A)**

TUMAS-A is focused on the open issues in inclusive learning environments to provide a personalized, accessible and ubiquitous support for their users (learners, facilitators, professors) using the appropriate technologies and standards as well as the evaluation procedures that can measure the impact of the personalized and inclusive support for all, but considering their individual and evolving needs, in their particular context.

# Adaptive Activities for Inclusive Learning using Multitouch Tabletops: An approach

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**Abstract.** People with cognitive disabilities have some difficulties with memory, literacy skills, attention and problem solving. Computers and specifically, adaptation mechanisms can be used to improve their learning. The adaptation allows fitting the learning process to each user. This paper presents a proposal to adapt learning activities while people are interacting using multitouch tabletops. The adaptation mechanism takes into account structural aspects, content adaptation and the interaction provided.

**Keywords:** Multitouch tabletops, adaptation, learning, Down syndrome.

## 1 Motivation

Some of the main categories of functional cognitive disabilities include deficits or difficulties with memory, literacy skills, attention and problem solving [1], and often visual or motor impairments. People with cognitive limitations have troubles to comprehend and to perceive the environment. They have difficulties with the transfer and consolidation of learning. For this reason, in the context of learning, new concepts to learn and problems to solve should be contextualized in daily situations to help learners to transfer knowledge to the real world. Furthermore, people with cognitive disabilities need concepts to be presented in a repeated and flexible way in order to assimilate them. Finally, due to their attention difficulties they can feel frustrated and disoriented if activities are monotonous or their level of difficulty is higher than their capabilities to solve them. As an example, unnecessary items should be deleted as they may distract the user and increase the difficulty of the task.

Computers offer valuable assistance to people with special needs, including those with physical and cognitive limitations [2]. Hardware (e.g. special Braille displays for users with visual disabilities) and software applications (e.g. speech output, word prediction, speech recognition software, etc.) contribute to this goal. They offer new opportunities to learn, share information and gain independence [3]. However, designing human-computer interfaces for users with disabilities is a challenging task [4]. Brajnik [5] grouped the WCAG 1.0 guidelines by their impact on specific user groups: blind, low-vision, deaf, color blind and physical handicapped users, as well as people with cognitive disabilities. Nevertheless, these guidelines are not enough in several cases being incomplete and not covering some of the user's needs [6].

Adaptation methods and techniques can contribute to adapt existing software to better suit the user's needs [7]. In the context of HCI, Universal Access introduces a new perspective recognizing values and attempts to accommodate a wide range of human abilities, skills, requirements and preferences in the design of computer-based products [8]. This implies an effort to design products and applications that can adapt themselves to suit the broadest possible end-user population. In this direction, there is a need to model user features for adaptation purposes [9]. Adaptive techniques are used in different application areas. Regarding systems focused on helping users with special needs, the first one to employ adaptive techniques in order to ensure accessibility and high-quality interaction for all potential users was AVANTI [10]. This system aimed to address interaction requirements of individuals with diverse abilities, skills, needs and preferences, using Web-based multimedia applications and services. Other example is the adaptive e-learning system presented in [11]. It provides adaptation to users with problems in mental programming (i.e., showing difficulties in organizing tasks or in figuring out problem solving strategies). Finally, regarding social abilities, Sc@ut [12] is used for improving social integration of people with temporary or permanent communication difficulties, specifically of autistic children.

## 2 The Approach

We are currently working on a project for adaptation of educational activities in multitouch tabletops to Down syndrome people. An activity is composed of a set of tokens distributed over common areas (shared by all the students) and individual areas (particular to each student). Activities can be performed either individually or collaboratively, affecting this to the token distribution. Two types of activities have been defined to this point: simple or multiple selection, and pair matching. Using FLING (*Flash Library for Interpreting Natural Gestures*) [13] to interpret multiple-finger input into meaningful gestures, we allow people to interact mainly through natural gestures using their fingers. In the case of simple or multiple selection activities in which users are given a set of tokens from which to chose according to a global question or statement, selection is done by touching the tokens directly with the finger. In the case of pair matching activities, in which users have to correctly associate tokens according to a global criteria, the interaction will be performed by default by drag and dropping one token over its paring one. Additionally, activities are grouped into projects: a set of activities that will be performed either sequentially or randomly.

In order to provide adaptation, user's information is stored in a user model comprising both static information, such as the background information, previous experience, motor functionality, visual impairments or index scores representing the major components of intelligence (verbal comprehension, working memory, perceptual organization and processing speed) [14], as well as dynamic information, such as physical location of the users or their evolution over the learning process (e.g. activities performed, results obtained, etc.). Dynamic information is updated according to the users' interactions with the tabletop.

Adaptation is then supported by means of rules mostly based on the recommendation mechanism of CoMoLE [15] in which an activation condition could be associated to the rules. Rule activation conditions determine for which users the rule will be applied. If an activation condition is not defined, the rule will be always triggered. There are three different adaptation rules:

1. *Structural rules* allow defining the different activities associated to a project and their accomplishing order (sequential or random).
2. *Individual requirements* are specific restrictions related to the accomplishment of a specific activity.
3. *Content adaptation rules* define how to adapt contents and to change the default interaction characteristics according to an activation condition (if any) and the activity type.

For example, learning activities can be adapted according to the users' previous background with multitouch tabletops, motor function ability (if they have mobility problems or not) and their results of previous activities. Additionally we may have a project (A) composed of six learning activities: a demo, to show how they can interact with the device (B), two simple selection activities (C, D), a multiple selection activity (E), a pair matching activity (F) and a review activity (G).

We have defined two different structural rules based on the users' previous experience with tabletops (see table 1). The first time students interact with the tabletop (see structural rule ①) they have to see a demonstration and to perform the selection activities (C, D and E), performing afterwards the review activity (G). However, if all the students have previous experience with the device, all activities but the demonstration will be performed (see structural rule ②).

**Table 1.** Example of two structural rules. Activation condition defines when the rule is applied and the guidance column specifies a sequential accomplishing order.

	Activation condition	Guidance	Activity	Subactivities
①	Background=no	Direct	A	B, C, D, E, G
②	Background=yes	Direct	A	C, D, E, F, G

As an activity G is a review of all previous activities, we can specify that students will only perform it when their results are lower than 7 (see table 2).

**Table 2.** Example of a specific requirement affecting to the subactivity G from the list provided by the activated structural rule.

	Activation condition	Activity
①	Results < 7	G

Finally, we have defined two content adaptation rules (see table 3). The rule ① changes the default interaction of the pair matching activities (drag and drop) when the user has motor function problems. In this case, the user should sequentially click over the elements to be matched instead of drag and dropping. The second content

adaptation rule establishes that the contents of our three types of activities must be resized when the user has visual impairments.

**Table 3.** Examples of two content adaptation rules.

Activation condition	Types of activities	Content Adaptation
① Motor_function = low	Pair_matching	Interaction = click
② Visual_impairment > 25%	Simple_Selection, Multiple_Selection, Pair_matching	Content_size = big

Thus, the user model can affect to the list of activities to be performed and the order in which they are performed as well as the interaction and presentation modes. Now, we have to consider too that several users may be interacting simultaneously on the same surface. In this situation, each student may tackle the project individually, thus activities will have to use only individual areas since common areas will otherwise have to match the different activities that are concurrently running. Conversely, a collaborative project requires a group model combining the features of each student involved in the activity. In this way, activation condition will refer to group features rather than to individual ones. An aggregation policy determines how group features are obtained as the combination of the corresponding features of each student involved in the activity. We have defined different policies to be selected by the teacher: highly restrictive, less restrictive, by majority and by minority. Thus, in a highly restrictive policy, the group feature takes the value of the lower (i.e. more restrictive) individual value, as in the majority policy the group feature takes the most common value among the students.

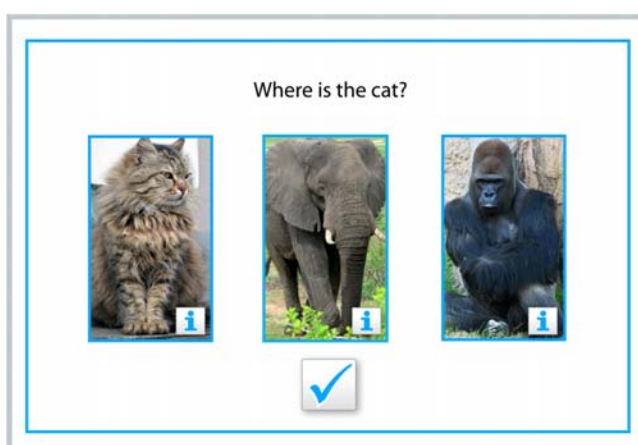
All adaptation capabilities can be defined using an authoring tool. This authoring tool is based on the CoMoLE's web-based authoring tool. Figure 1 shows a snapshot of this tool where the teacher can define the features to be considered in the adaptation mechanism.

**Fig. 1.** Snapshot of the authoring tool.

In addition, feature values can be either numerical or stereotypes. If a characteristic is numerical, its value can range between a defined minimum and maximum

thresholds. If stereotyped, it is necessary to specify two or more possible values from which the characteristic will be chosen. In order to ease the process to teachers, the most common useful features are already added to this tool. Adaptation capabilities are defined with this tool too.

Once the teacher has defined all the adaptation features to be considered, students will use the D2-Player to perform the activities. The adaptation mechanism presented in this section is implemented in an external module responsible of selecting the most suitable activities and contents for the users around the tabletop. Figure 2 shows an example of a student area for a simple selection activity using the D2-Player (the D activity of the previous example).



**Fig. 2.** Example of a simple selection activity generated by the authoring tool and reproduced in the D2-player. The final presentation is adapted according to the user profile.

Aiming to help teachers, this area is automatically replicated to the number of students around the tabletop, from one to four. In this case, the teacher does not need to explicitly specify any type of adaptation.

### 3 Conclusion and current work

This paper presents a proposal to adapt activities in inclusive learning environments using multitouch tabletops. The adaptation is based on a recommendation mechanism previously applied to mobile learning systems. When working with users with cognitive disabilities, it is really important to adapt activities to their main features both individually and collaboratively.

This project emerged from the collaboration between the Fundación Síndrome de Down de Madrid and the researchers of the ASIES project. Teachers from this foundation are really interested in the development of educational tools to design adaptive learning activities for multitouch tabletops as this type of devices are physical spaces strongly promoting collaboration.

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# Personalization Of Mobile Learning Tools For Low-Income Populations

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**Abstract.** The ubiquitous presence of cell phones in emerging economies has converted them in ideal platforms to cater services for underserved communities in areas like mobile learning. M-learning tools have proved successful in such challenging environments, specially for afterschool and vocational programs. A key component of that success is the personalization of the tools to the community and to particular individual needs. However, in order to tailor contents to the students, we first need a deep understanding of their learning abilities and preferences. Our findings show that there exist statistically significant differences in learning behaviors across gender and age. Finally, we propose a set of design suggestions that, based on the differences observed, attempt to personalize and adapt the mobile learning tool under study to enhance its educational impact in the low-income community.

## 1 Introduction

There exists a large collection of mobile learning tools for low-income communities adapted to all types of cell phones, mostly deploying SMS- or Java-based solutions to deliver educational content [1]. Our research focuses on the personalization of such educational tools, which is specially critical in emerging economies where access to education tends to be more limited and irregular. As a result, students with similar ages might show very different levels of achievement and could thus benefit from personalized contents. The delivery of personalized education is complex because the adaptation to each individuals' requirements demands a deep understanding of their abilities and preferences. Related work in the areas of e-learning and tutoring systems has demonstrated that demographic factors and learning capabilities play an important role in knowledge acquisition [3]. Nevertheless, very little work has been done to understand which factors impact the learning process in the area of mobile learning for low-income communities [4]. In this paper, we present an evaluation of the repercussion that gender, age and individual learning abilities might have on the successful use of *EducaMovil* in a low-income community [5]. For that purpose, we carry out statistical and clustering analyses to reveal specific behavioral traits across the students in the low-resource school. Additionally, we use these findings to provide design guidelines for the personalization of our mobile learning tool prior to a future long-term evaluation of its educational impact.

## 2 EducaMovil Architecture

EducaMovil is a system that has two main components: (1) a PC tool for educational content creation and (2) a mobile game-based educational application for Java-enabled cell phones [5].

### 2.1 PC Tool

The PC tool allows teachers to create the educational snippets that will be shown in the mobile game. Each educational snippet is composed of a lesson and a quiz, although only quizzes are also possible. The lesson typically contains an image and/or an explanation about a specific concept. A lesson is always followed by a quiz, which is a test question that the students are required to answer in order to evaluate their knowledge acquisition. For that purpose, student answers are compared against the correct quiz answers given by the teachers while creating the lessons. Additionally, teachers are required to label each educational snippet with its educational level (1st to 6th in primary school or 1st to 5th in secondary) and a complexity level (five levels from very easy to very difficult).

### 2.2 Cell phone Tool

The mobile phone application that students run on their cell phones consists of two elements: the game and the educational snippets created by the teachers. EducaMovil offers the possibility of embedding the educational contents into different open-source games for cell phones like Snake, Tetris or Rally. The games are modified to add a module that handles the management of the educational contents. This module consists of three components: Game Model, Adaptation Model and User Model.

The *game model* is responsible for the interaction between the open-source game and the educational snippets created by the teachers. The game model is fired every time an event in the game allows players to win points (or lives) and introduces the educational snippets as the units that need to be solved before winning the points. After the student finishes exploring the lesson, s/he will be prompted with a quiz, which is based on the lesson's content. If the learner provides a correct answer to the quiz, s/he receives an award in the form of lives or points.

The *adaptation model* determines the specific educational content that is going to be shown to the student at each step of the game. Recall that each educational snippet is labelled with its educational level and a complexity level. The adaptation model selects, for a specific educational level, the complexity of the educational snippet that is going to present to the student next, based on the students' past learning evolution. In our strategy, students that answer correctly to at least 60% of the questions for a specific complexity level, are shown quizzes from the next level until the maximum complexity (*very difficult*) is reached. If the student reaches the maximum level of complexity for her educational grade, the game ends. Questions for each complexity level are randomly selected across all academic subjects.

The *user model* stores the interactions of the student with the educational units and the game. The model keeps counters about the lessons explored by the student, whether the quizzes were answered correctly or not, time invested to answer quizzes, and the complexity level reached. This model is primarily used by the adaptation model to determine the complexity level of the lesson/quiz to be shown next.

### 3 Experimental Procedure and Data Collection

The evaluation of EducaMovil consisted of one-on-one sessions where each student sat down and received an initial description of the game, its rules, the educational snippets and how to navigate through these with the cell phone. After the initial introduction, we let the student play for 20 minutes. During the session, students were shown educational snippets from their own educational grade starting with easy lessons which evolved in complexity based on the adaptation model. A total of 27 students from a low-resource school in Lima (Peru) tested EducaMovil: 5 from each 1st, 2nd and 3rd years and 6 students from each 4th and 5th years of the secondary school. These students had ages between 12 and 16 and in terms of gender, 15 were female and 12 male. At the end of each session, we collected a user model with the student interactions and computed a *general performance model (GPM)* for each student  $i$  as  $GPM_i = (C, T) = (100 * (\sum_{j=0}^n A_j)/n, (\sum_{j=0}^n T_j)/n)$  where  $A_j$  is the answer given to question  $j$ ,  $T_j$  the time used to answer it and  $n$  represents the total number of lessons explored by the student.

### 4 Analysis and Game Design Implications

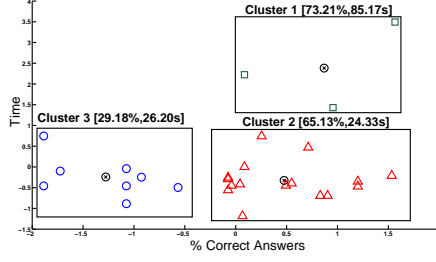
We carry out two types of analysis: (i) analyze whether there exist differences in the learning performance of the students based on gender or age and, (ii) evaluate the types of learning behaviors observed across all students. The first analysis will give us suggestions for gender- or age-based personalization. As for the second, it will provide design guidelines to personalize education based on *stereotypes i.e.*, learning behaviors shared by groups of students [2]. Although the results are preliminary and specific to our pilot, the techniques proposed can be used to guide the personalization of any mobile learning tool.

**Gender and Age** In order to understand whether gender or age impact the learning interactions of the students with the tool, we build gender- and age-based distributions for each performance variable (percentage of correct answers  $C$  and average time per lesson  $T$ ) and compute statistical tests to understand whether the differences we observe are statistically significant or not. Given that our distributions are small (27 student models), we report results for non-parametric statistical methods to avoid assuming a normal distribution for a dataset that might not be sufficiently large. To carry out the **gender analysis**, we first compute the female and male distributions separately for each performance variable  $C$  and  $T$ . To test the differences between each pair of female-male distributions we use the *Kolmogorov-Smirnoff test* and, given the small

number of samples we have, reject the *null hypothesis* whenever  $p \leq 0.1$ . Our results show that the percentage of correct answers for females is higher than its male counterpart and statistically significantly different ( $p = 0.08$ ). Specifically, the female distribution had an average percentage of correct answers of 58.4% ( $\sigma = 18.3\%$ ) and the male had an average of 50.2% ( $\sigma = 15.9\%$ ). On the other hand, we also observe that the female average answering time per quiz is also higher than its male counterpart and statistically significant ( $p = 0.1$ ). Females showed an average answering time of 36.4s ( $\sigma = 16.3s$ ) and males had an average time of 24.7s ( $\sigma = 13.3s$ ). These numbers show that female students achieve statistically significant higher percentages of correct answers ( $\approx 8\%$  more) but need more time to answer the quizzes ( $\approx 12s$  more on average). This fact is not necessarily bad if it is related to women being more thoughtful, but could be harmful if connected to a lack of confidence. In an attempt to decrease answering times while maintaining performance, we suggest to put counters and timers in the quizzes so as to create a healthy competition between men and women not only in terms of correct answers but also in terms of answering times.

To perform the **age analysis** we compute for each performance variable  $C$  and  $T$  one distribution per educational level (age). To understand whether there exist differences in the student performance across educational levels (age groups), we run *Kruskal-Wallis* tests for each group of five distributions representing the five age groups present in the pilot. We reject the *null hypothesis* with  $p \leq 0.1$ . Our results determined that there exists a statistical significant difference between the percentage of correct answers among some of the five educational levels with  $p = 0.05$ . However, we do not observe any statistically significant differences on the average answering time. We observe that students from the 3rd grade outperform all their peers with an statistically significantly different percentage of correct answers (*median* = 85%), whereas students from the first grade show the worst performance with a median value of 29%. This analysis shows that although students are shown quizzes adapted to their own educational level, not all groups respond equally. In fact, we observe that students from educational levels 4th and 5th are statistically significantly outperformed by the students in the 2nd and 3rd grades. This might be related to learners in their last school years being allowed to move to the next educational level without making sure they have acquired the minimum required knowledge. We suggest to add quizzes from previous educational levels until the students show an improvement in their performance. This approach will allow them to review previous contents and to eventually reach their own educational level.

**Stereotypes** In this section, we use the *k-means* clustering technique to identify common learning behaviors (*stereotypes*), independent of age or gender, among the students in our study. Given that the final k-means partition highly depends on the initial seeds selected, we run the algorithm 100 times for each value of  $k$ , and select the cluster distribution with the most compact and well separated clusters *i.e.*, the one with the minimum *cluster validity index* computed as the ratio between the intra-cluster distance and the inter-cluster distance among all sample. Once the best selection of clusters has been identified for each value of  $k$ , we select the  $k$  with the smallest cluster validity index across all partitions



**Fig. 1.** Student stereotypes with  $k = 3$  (axes represent normalized values).

evaluated (from  $k = 2$  to  $k = 7$ ). In practical terms, we attempt to find clusters of common performance behaviors across the 27 GPMs. For that purpose, we normalize across all GPMs, apply k-means and validate for each value of  $k$ . Although the minimum cluster validity index corresponds to  $k = 2$ , we discuss  $k = 3$  since it provides more insight into the learning stereotypes than  $k = 2$ . Larger values of  $k$  have larger cluster validity indices and do not provide any other relevant information after exploration. Figure 1 shows the results for the clustering of the 27 GPMs with  $k = 3$ . *Cluster 1* with centroid (73.2%, 65.1s) and three students represents a group with the highest percentage of correct answers and the largest answering times. Interestingly enough, this group contains only female students. *Cluster 2* with centroid (65.1%, 24.3s) and 15 students, represents a group that employs little time to give the correct answers. This cluster probably groups the best students. *Cluster 3* with centroid (29.1%, 26.2s) represents a group of 9 students that share a low percentage of correct answers and low average answering times. This group probably represents students who answer randomly with their interest devoted to the game instead of the educational contents. We suggest that when this type of behavior is identified on a specific student, the game should be slowed and show more than one quiz at a time to force the student to focus on the quizzes.

## 5 Implications for Game Design

Our analyses have identified learning behaviors that can be used towards the personalization of EducaMovil. Although these findings cannot be extended to other low income communities and learning tools, similar analytical techniques could be used to propose different personalization suggestions. The *gender analysis* highlighted that although women tend to perform better than men, they generally need longer answering times. This fact is not necessarily bad if it is related to women being more thoughtful, but could be harmful if connected to a lack of confidence. In an attempt to decrease answering times while maintaining performance, we suggest to put counters and timers in the quizzes so as to create a healthy competition between men and women not only in terms of correct answers but also in terms of answering times. The *age analysis* showed that students from the last years of secondary education (4th and 5th) performed worse

than their younger counterparts. This finding could be related to students being promoted to the next level without having acquired the minimum knowledge for their current grade. In this sense, we suggest to add quizzes from previous educational levels until the students show an improvement in their performance. This approach will allow them to remember or review previous contents and to eventually reach their own educational level. Finally, the *stereotype analysis* revealed, among other things, that there exists a group of students that answer the quizzes almost randomly so as to advance on the game, without showing any interest on the educational content (identified as *Cluster 1* in our analysis). We suggest that when this type of behavior is identified on a specific student, more than one quiz at a time should be shown before going back to the game; and the game itself should be slowed until it becomes boring and forces the student to focus on giving better answers to the quizzes.

## 6 Conclusions and Future Work

A very important component of mobile learning services is the personalization of the educational tools, specially for low-income communities. Research has shown that personalization to tailor content and structure highly increases the quality of the learning tools and enhances the learning process. However, in order to do so, we need a deep understanding of the abilities and preferences of a learner. In this paper, we have proposed a series of techniques to model learning performance and understand the impact that gender, age or learning behaviors might have on the learning process of the students in a low resource school in Lima, Peru. For that purpose, we have run a pilot with *EducaMovil*, a game-based mobile learning application for afterschool programs in low-income schools [5]. The pilot program, which ran for two weeks, allowed us to gather a varied range of student interactions with the game. We have proposed improvements to the design of *EducaMovil* so as to personalize and adapt the tool to the learning behaviors identified in our analysis. Although these results might not be applicable to other low-income schools or other socio-economic levels, the set of techniques can be used across all scenarios. In the future, we will modify *EducaMovil* to include the design implications discussed and we will carry out a long-term evaluation of the learning tool for a large group of students during a full semester.

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# Open issues in personalized inclusive learning scenarios

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**Abstract.** This paper discusses some of the existing open issues in personalized inclusive learning scenarios that are being worked in the context of A2UN@ and ALTER-NATIVA projects by a joint collaboration among the aDeNu research group at UNED and the BCDS research group at the University of Girona.

## 1 Introduction

Accessibility, adaptation and learning are three interrelated issues with a growing interest in our society. Unfortunately, in Higher Education (HE) institutions, Information and Communications Technology (ICT) services are still not fully accessible to an increasing number of students whose main educational option is distance learning (in Spain roughly 50% of students with disabilities select distance learning).

At the aDeNu research group (which stands for ‘Adaptive Dynamic online Educational systems based on User modelling’) of the UNED (Spanish National University for Distance Education) we have been actively involved in providing personalized and accessible services for life long learning [1]. In turn, the BCDS (which stands for ‘Broadband Communications and Distributed Systems’) at the University of Girona focuses on adaptive models for collaborative distance learning and dynamic adaptive hypermedia systems. In order to tackle the open issues in personalized inclusive e-learning (PIL) scenarios both groups are jointly researching in the context of the A2UN@ and ALTER-NATIVA projects.

A2UN@<sup>1</sup> is a research project (TIN2008-06862-C04-00/TSI) funded by the Spanish Ministry of Science and Innovation and stands for Accessibility and Adaptation for ALL in Higher Education. A2UN@ objective is to analyze the

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<sup>1</sup> A2UN@: <http://adenu.ia.uned.es/web/en/projects/a2un>

capability of developing a general framework based on standards and user modelling, to support the development of the lifelong learning services required to attend the accessibility and adaptation needs for all in the university context, with special attention to the diversity of requirements of adult learners and those who have the so-called disabilities. In particular, the key objective of A2UN@ is to develop the required interoperable and layered-based infrastructure to facilitate the definition, development, deployment and evaluation of the services to be provided for supporting accessible and personalised learning in higher education [2].

ALTER-NATIVA<sup>2</sup> is a research project (DCI-ALA/2010/88) funded by the European Commission ALFA III program to stimulate the improvement of quality in higher educational institution in Latin America. The main objective of this project is to support teachers of diverse subjects (e.g. language, arts, science and mathematics) in their educational tasks to cope with learning contexts with diversity requirements (such as accessibility, multi-linguism, poverty, forced displacement, etc.) by means of ICT as a key element in the learning process.

In this paper, we introduce the open issues identified in the context of the A2UN@ and ALTER-NATIVA projects and the research works carried out in them to support PIL scenarios.

## **2 Open issues and research in the A2UN@ project**

In the context of the A2UN@ project, the following open issues have been identified [2]:

1. The need of support for describing and managing accessible and adaptive learning scenarios.
2. The existence of overlapping and contradictions between available standards to manage accessibility issues and dynamic support in terms of i) users' models, ii) learning scenarios, iii) interaction preferences, iv) devices capabilities, and v) metadata for specifying the delivery of any resource to meet users' needs.
3. The lack of frameworks for providing layered-based infrastructure covering the interoperability required to manage the whole range of standards, applications and services needed to meet accessibility and adaptations needs of lifelong learning services.
4. The availability of limited research on constructing adaptive learning scenarios to manage accessibility issues (including artificial intelligence techniques such as machine learning, web-mining, and multi-agent systems).
5. The shortage of best-practices in developing and providing accessible and adaptive learning scenarios that counts with the participation of different types of users on the demand side (students with special needs) and different existing roles on the supply side (administrators, faculty staff and specialized support people in providing the services).

Several works have been carried out to address those issues and support PIL scenarios in the context of the A2UN@ project. First, we have analysed the existing support

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<sup>2</sup> ALTER-NATIVA: <https://adenu.ia.uned.es/web/en/projects/alter-nativa>

offered by standards and specifications that impinge on accessibility issues regarding users' models, learning scenarios, interaction preferences, devices capabilities, metadata for specifying the delivery of any resource to meet users' needs, and software accessibility and usability [3]. This work has confirmed the lack of standards that are oriented towards users and developers, and also addressing all areas of modelling treated, as well as the existence of many conflicting standards that address the same issues but with different views. Another study focuses on standards supporting the interaction between the user and the e-learning system also reports that today there is no single standard able to model this context and the application of a combination of several of them results in overlaps and gaps [4].

Moreover, the research has also focused on building a user model for students performing learning processes in virtual learning environments that manages the cognitive performance of each student considering four cognitive areas related to the attention capacity (i.e. verbal learning, working memory, concept shifting and sustained attention) [5,6].

Furthermore, in conjunction with the EU4ALL project, we have researched and developed a flexible framework to cope with different scenarios for inclusive learning designed to support the needs of the stakeholders involved, both students and professionals [7]. This framework uses existing standards to define and implement an open and extensible architecture of services for accessible lifelong learning.

We have also coined the concept of Semantic Educational Recommender Systems (SERS), which based on educational criteria, guide learners in their interaction within e-learning platforms by providing personalized and inclusive recommendations that could target any possible actions within an e-learning platform [8].

### **3 Planned research in ALTER-NATIVA**

ALTER-NATIVA project has two different and important dimensions to be addressed, that is, the pedagogical and the technological dimension. The principal objective of the pedagogical dimension is to define a set of referents or guidelines which could be used for teachers in order to apply the most common technologies in the learning process. In turn, the technological dimension must address the educational contextual diversity existing in a virtual learning environment taking into account the most relevant features of the system actors such as students and teachers. In this context, educational needs on diversity are understood as the result of physical, physiological, sensorial or social conditions that put people in special situation for accessing knowledge, cultural or social relationships.

Based on previous experience in the A2UN@ project, the technological developments of the ALTER-NATIVA project focuses on three major research and development lines: i) the user modelling process, ii) the learning objects construction and labelling, and iii) the generation of adaptive learning experiences to meet user needs represented in the model. Moreover, the ALTER-NATIVA project takes advantage of the diversity of the specialists in different field of people behaviour to address user and context modelling processes not consider in the A2UN@ project.

Moreover, ALTER-NATIVA addresses some other open issues. In particular, Latin American culture poses special conditions such as multi-lingualism, which is defined by the presence of different indigenous communities that have preserved their language over time. In particular, Mexico and Bolivia count with 87 different languages. This fact expresses the importance of the inclusion of user model features related with the language such as reading or writing ability, or the possible reduction of this ability because of the use of a second language or cognitive traits involved in a multi-lingual educational process. Thus, the Latin America special social context requires knowing special access conditions, not limited only by the technologies available but by poverty and forced displacement, among others. These conditions must be identified and represented. It is our intention through an intensive context modelling to consider the necessary dimensions to support Latin American Education.

Populations with disabilities are also considered in the context of ALTER-NATIVA project. The state of the art considers the identification and evaluation of assistive technologies to enhance learning process for people with visual and hearing disability and people with Attention Deficit Hyperactivity Disorder (ADHD) symptoms. User modelling and adaptations based on machine learning techniques, image recognition and augmented reality have been considered.

Another important issue to be covered by this project is the construction of accessible learning objects to support the learning process. ALTER-NATIVA validation scenarios consider a special population, which are students learning to become teachers which aim to teach math, science and languages. In this way, the methodology of appropriation of learning objects focuses on two important issues. On the one hand, the existence of distributed learning objects, which should be retrieved smartly; and on the other hand, the construction itself of the specific accessible learning objects. To address the first issue agent-oriented methodologies have been considered in order to achieve federated searcher engines. For the second issue, Web Accessibility Guidelines 2.0 (WCAG 2.0) have been considered. Hence, user modelling process and accessible learning objects are the bases for delivering adaptive learning experiences to users. These experiences include adaptive learning path, adaptive games, and adaptive grouping experience, among others.

## 4 Summary

In this paper we have presented the works carried out by aDeNu and BCDS research groups aimed to support PIL scenarios. These works are framed in the context of A2UN@ and ALTER-NATIVA projects. In the former, we have identified five open issues and have worked on several dimensions to address them, such as the analysis of existing standards, the building of user models, the definition of educational services and the application of semantic educational recommender systems. In the ALTER-NATIVA project (just started) we will continue working on those issues to support teachers of diverse subjects (e.g. language, arts, science and mathematics) in their educational tasks to cope with learning contexts with diversity requirements (such as accessibility, localisation, etc.) by means of ICT as a key element in the learning process.

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