What's next? Different Strategies Considering Teachers' Decisions for Adapting Learning Paths in Serious Games

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Abstract: Adapting Serious Games (SGs) plays an important role to offer personalized game experiences. A well-fitting approach to create adaptive SGs is based on Competence-based Knowledge Space Theory (CbKST). CbKST structures the SG activities with respect to knowledge and competences, and adaptation is based on suggesting activities that improve learners' competences. However, differences among learners and the diversity of learning situations may drive teachers to use different adaptive approaches to address their own needs. In addition to the current state of learners' competences, we also propose to consider teachers' decisions as a key parameter for adapting learning paths in SGs. As part of Play Serious project, several teachers' requirements have been identified. This paper presents three different recommendation strategies based on the identified requirements, to build adaptive learning paths in SGs.

1 INTRODUCTION

Adaptation is considered a key issue in Technology-Enhanced Learning (TEL) since learners are not alike; they have different knowledge and skills, as well as learning preferences, interests and attitudes. The motivation for employing adaptive assessment is that learners come to new learning tasks aligned with their profiles (Shute and Zapata-Rivera, 2012). Taking full advantage of such assessments requires the use of adaptive techniques that yield information about the student's learning process and outcomes.

In Serious Games (SGs), adaptation is based on decisions that suggest activities in such a way that the learner is neither unchallenged nor overwhelmed by the complexity of the contained tasks (Göbel et al., 2010). As a consequence, learners become less frustrated and their motivation is increased (Hocine et al., 2011).

Competence-based Knowledge Space Theory (CbKST) has been proven to be a well-fitting basis for realizing adaptation in SGs (Augustin et al., 2013). This methodology allows a non-invasive assessment of the learner without interrupting the game flow experience (Kopeinik et al. 2012). CbKST allows modelling a knowledge domain as a formal structure of admissible and meaningful *competence states* on the basis of *precedence relations* among the competences. In other words, CbKST formally structures the activities of an SG with respect to knowledge and competences (Heller et al., 2006; Kopeinik et al., 2012). The SG activities are related to the competences worked on. Learners have to demonstrate that they master these competences by performing the tasks contained in the different SG activities. To this end, systems compute confidence values, linked to learner's competences that represent learners' proficiency level. These confidence values are used as main parameters in the adaptation rules.

In this work, we propose to also consider teachers' decisions as a key factor for adapting SGs in order to address specific pedagogical needs. Learners have different range of abilities, needs and interests, and teachers may consider implementing different approaches that fulfil their needs (Marne and Labat, 2014; Santangelo and Tomlison, 2009; Shute and Zapata-Rivera, 2012). In other words, teachers' decisions could be based on the variety of teaching styles, learners' knowledge and performance, learning styles, and learning contexts (Moreno-Ger et al., 2009; Shute and Zapata-Rivera, 2012).

Therefore, we propose to enhance adaptation in SGs by considering not only the learner's *competence states* but also teachers' decisions based on their needs. More specifically, we have identified different teachers' needs concerning the possibility

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of allowing their students' to advance forward learning paths of SGs, as well as to reinforce and deepen specific subsets of competences. Therefore, in this paper, we propose different recommendation strategies and we describe how we implemented these strategies by using CbKST.

The remainder of the paper is structured as follows. In section 2 we introduce the context of this work, describing the identified teachers' needs for adapting SGs. We also describe the basis of this work that relies on Competence-based Knowledge Space Theory. In section 3, we present the recommendation strategies considering the identified needs presented in the previous section. In Section 4, we describe a preliminary evaluation on the proposed strategies. Finally, in section 5, we conclude with a discussion of the proposed approaches, as well as future research directions.

2 CONTEXT

2.1 Teachers' Needs in Adaptive SGs

This work is framed in the Play Serious Project (Play Serious, 2013). The purpose of the project is to develop tools that facilitate the design and development of SGs in the field of adult vocational training. The proposed tools are classified into three different categories:

1. Authoring tools for supporting the development of SGs (e.g. SG scenarios).
2. Monitoring tools for analyzing learning actions and assessing learners' competences.
3. Adaptive tools for modifying learning paths of SGs.

This paper particularly focuses on advancing forward the development of adaptive approaches for serious games (3rd category of tools). In this context, different strategies for adapting SGs have been identified from the joint work with pedagogical experts and teachers involved in the project. Teachers and pedagogical experts from different companies (e.g. sales market) express their needs to deploy some pedagogical strategies. The identified requirements and proposed strategies are described as follows:

S1. The first requirement is related to allow learners progressing autonomously and gradually to achieve all competences of a knowledge domain. The competences have to be worked on at the end of the training session. To meet this requirement, we define the "**Advancing**" strategy. This strategy considers the learner's proficiency level and proposes activities that work on the maximum number of competences. At each step the proficiency level is updated allowing a progression in the learning path until all competences have been worked.

S2. The second requirement focuses on training sessions that are divided into stages. Given a stage, teachers aim to specify a subset of competences to work on, as well as the degree of achievement as prerequisites to let their learners move forward in the following stages. For instance, in the step "common ground" in sales training, competences that have to be worked to move forward in the following stage include "identifying customer needs", "collecting information about the customer". To meet this requirement, we define the "**Reinforcing**" strategy. This strategy allows the learner to reinforce specific competences that have not met a minimum threshold. This case arises when these competences are needed/required in the next stage of the training course.

S3. The third requirement is to offer teachers with the possibility to choose specific competences to let the learners to progress to a higher advanced competence level. Teachers aim to identify learners that are very good in specific competences. The teachers' intention is to lead these learners achieve a very high level in those competences to become quickly operational within the company. For instance, in sales enterprises, trainers could seek for employees that are outstanding in "treating customer objections" or "arguing different solutions to meet the client's needs" in order to become managers of sales team. To meet this requirement, we propose the "**Deepening**" strategy. This strategy allows learners to become expert in certain competences that they have already mastered within a knowledge domain. One competence has been mastered when the proficiency level is above a threshold value introduced by the teacher.

In order to implement the different strategies, the partners of the project focus on SGs that are based on activities that typically correspond to levels in SGs. These SG activities contain the tasks that learners can perform to train specific competences. Besides, SGs activities have to be independent from each other. The aim is to allow organising the SG activities in different ways and hence create diverse learning paths. Therefore, the SGs in the project can be considered as curriculum sequencing environments in the sense that learning paths can be defined as a set of independent entities that can be assembled in different ways (Brusilovsky and Vassileva, 2003).

As representative works of curriculum sequencing environments we can cite the adaptive hypermedia (Brusilovsky and Vassileva, 2003) or ALEKS (www.aleks.com), an environment of a commercial spin off of the University of California at Irvine. The concept of curriculum sequencing is grounded on Knowledge Space Theory (KST) (Falmagne et al., 2006). Thus, in order to provide with a feasible implementation for the different strategies, we based our work on KST, and more precisely on its extension: Competence-based Knowledge Space Theory (CbKST) (Heller et al., 2006; Korossy, 1999), as a potential framework for adapting learning paths in SGs.

2.2 Competence-based Knowledge Space Theory (CbKST)

CbKST is an extension of KST (Falmagne et al., 2006). KST was intended for the assessment of learners' knowledge. Advancements of KST introduce a separation of observable performances and the underlying abilities or knowledge, leading to diverse competence-based approaches (Reimann et al., 2013). CbKST relies on three main concepts: *precedence relations*, *competence states* and the *competence structure.* Basically CbKST assumes a defined set of competences and *precedence relations* between them. In other words, a *precedence relation* $a \leq b$ indicates that competence 'a' is a prerequisite to acquire another competence 'b'. Considering *precedence relations*, *competence states* are the resulting meaningful combinations of single competences. A *competence structure* is obtained by deriving all the admissible competence states of a certain domain. Figure 1 shows an example of *precedence relations* between five competences and the *competence structure*. In this example, the set {a, c} cannot be a *competence state* since competence 'b' is also required to master competence 'c'.

Given a *competence structure*, the lowest *competence state* represents the naive state (i.e. the learner has not mastered any competence yet) and the highest *competence state* represents the state in which the learner has mastered all the competences for a given domain. Then, a learning path represents a possible path in the *competence structure* that moves from the lowest *competence state* to the highest one.

There are diverse research works on adapting SGs based on CbKST (Augustin et al., 2013; Kickmeier-Rust et al., 2008; Kopeinik et al., 2012; Peirce et al., 2008). However, while the identified literature focuses on the traditional approach based on improving learners' competences, as far as we know there is a lack of research studies that consider teachers' needs as a factor when implementing adaptive SGs. For this reason, we also introduce teachers' decisions as an input to enhance adaptation in SGs.

In the next section, we describe the architecture to implement the recommendation strategies to suggest SG activities considering the requirements expressed by teachers.

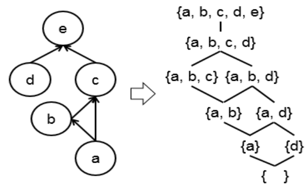

Figure 1: Example of *precedence relations* (left graph) and *competence structure* (right graph).

3 RECOMMENDATION STRATEGIES

We propose the development of a decision module based on an adaptation model proposed by Kopeinik et al. (2012) in order to implement the different recommendation strategies. Like Kopeiknik et al., we consider the learner's current competences. In addition, in our approach we consider the teachers' decisions that mainly deal with selecting one of the identified recommendation strategies. Also, we consider recreational competences of SG activities. The overall logic architecture of the decision module is depicted in Figure 2.

In order to implement the recommendation strategies and hence achieve adaptation, the decision module considers the following elements to suggest learning paths in SGs:

- The domain model of the SG. This means, the pedagogical competences and the links between competences. This information is used to build the *competence structure* based on CbKST.
- The recreational competences. Together with the domain model, these competences define the game requirements to a particular SG. The domain model and recreational competences do not change during the game process.
- The list of activities (or levels). Each activity can be linked to pedagogical competences, as well as recreational competences.

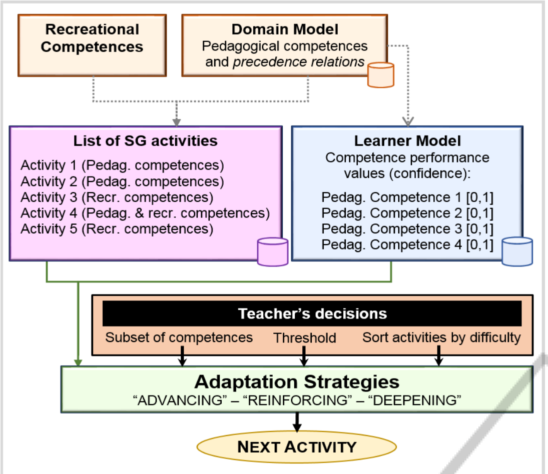

Figure 2: Logic architecture of the Decision Module.

An activity corresponds to a way to perform a task in an SG. In our work, we define an activity as a basic unit and it corresponds to a level within an SG.

- The learner model. This model keeps track of the activities performed by the learner and it stores the accumulated evidence about competences. This means, each competence has a value corresponding to the probability that a learner master this competence. Initially, a learner assessment is done before playing the game to initialize the confidence or probabilistic values. These probabilistic values are changing during the game playing (after the learner has finished each activity). As mentioned before in the section 2.1, in the context of the project, we also work on a monitoring tool that computes these probabilistic values. This work, which is out of the scope of this paper, extends a previous work (Thomas et al., 2012) by using Bayesian networks.
- The recommendation strategies that the teacher can choose. These are: a) "Advancing": suggests activities that address the same competences as those in the current learner's *competence state* and moves one step forward in the *competence structure*; b) "Reinforcing": suggests activities that address a subset of competences specified by the teacher. The percentage of accomplishment of the selected competences must be below a certain threshold (value that has to be reached by the learner for improving the competences in which he/she is weaker); and c) "Deepening": also suggests activities that address a subset of competences specified by the teacher. Unlike "Reinforcing" strategy, the percentage of accomplishment of the selected competences must be above a certain threshold value specified by the teacher. This value indicates that the learner is good in the set of competences and the teacher aims that he/she becomes better.

Next section focuses on describing the behaviour of the different recommendation strategies.

3.1 "Advancing" Strategy

The "Advancing" strategy addresses the first requirement identified in the Play Serious project that aims at working the maximum number of competences in a certain domain (S1).

This strategy considers the current learner's *competence state* and moves to the next *competence states* in order to propose an activity (see Figure 3, 1).

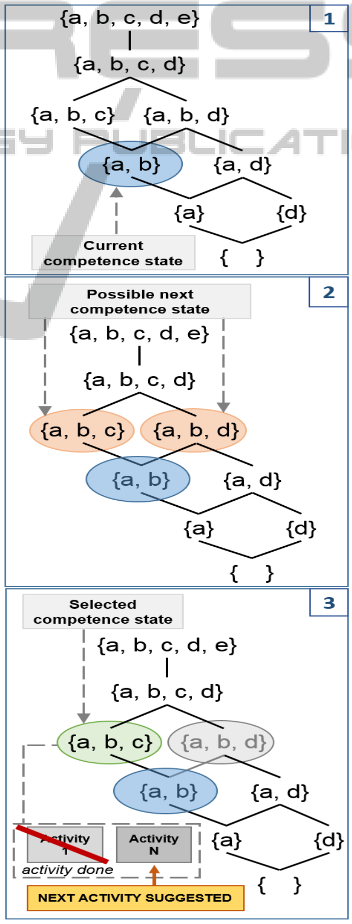

Figure 3: Graphical example of the behaviour of the "Advancing" strategy.

The next activity to be played is suggested as follows.

- First, we get the possible next *competence states*. Next *competence states* (i.e. successors) are those which contain exactly the same the competences of the current *competence state* plus one more (see Figure 3, 2). In CbKST, the additional competences in the successors are the *outer fringe* of the current *competence state*.
- Then, we iterate the list of the next *competence states*. For each *competence state*, we look at the associated activities that have not been done by the learner (see Figure 3, 3).
- If there are no activities (because there are no activities designed for this *competence state*), we move to the following *competence state*.
- If there are activities, we select one of them. The next activity is selected considering the difficulty level, if this option has been selected by the teacher. Otherwise, a random function is applied. Besides, if the pedagogical activity has recreational competences, then if possible, we suggest before an activity that only works the recreational competences (if the learner has not worked on these competences yet).
- If none of the next *competence states* contain activities, we look at higher knowledge states. This strategy finishes when the last *competence state* (containing all the competences) is reached.

3.2 "Reinforcing" and "Deepening" Strategies

The "Reinforcing" and "Deepening" strategies fit the second and third requirements identified in the Project, respectively. From an algorithmic point of view, the behaviour of "Reinforcing" and "Deepening" strategies is very similar, but they address different pedagogical needs. These are: providing the learner with activities to reinforce certain competences (S2), and with activities to become expert in certain competences (S3).

First, we consider the current learner's *competence state* and all previous *competence states* from the *competence structure* (see Figure 4, 1). The initial state of the algorithm considers the subset of competences selected by a teacher, as well as the specified threshold value. Then, from the subset, we get those competences that are below (in "Reinforcing" strategy) or above (in "Deepening" strategy) a certain threshold specified by the teacher (see Figure 4, 2).

From the selected subset of competences, the algorithm follows an iterative process.

- First, we get one competence from the subset of competences.

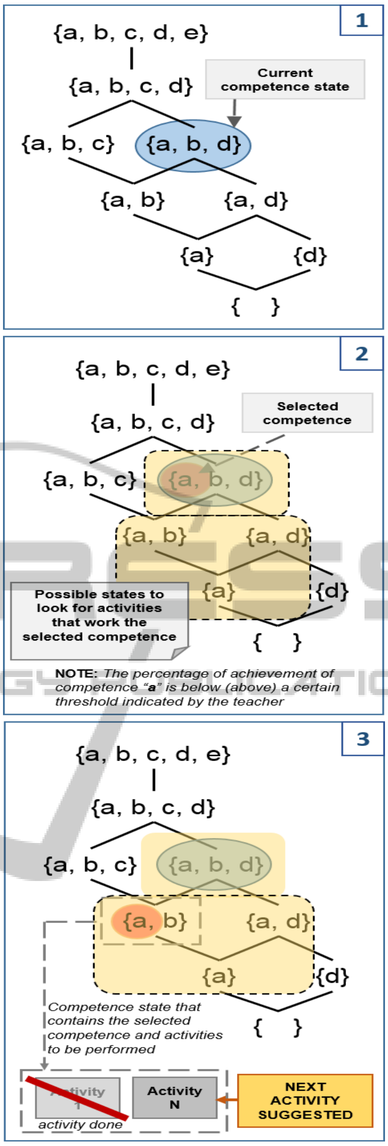

Figure 4: Graphical example of the behaviour of the "Deepening" and "Reinforcing" strategies.

- Right afterwards, we look at the previous *competence states* (from the initial to the current learner's state) that contain the selected competence to be worked (see Figure 4, 2).
- Then, for each of these *competence states* we get the activities that have not been done yet (see Figure 4, 3).
- Similarly to the "Advancing" strategy, if there are several activities linked to the *competence state*, we select the next activity considering the difficulty level if specified by the teacher. Otherwise, a random function is performed to suggest the next activity. Besides, if the selected pedagogical activity has recreational

requirements, then if possible, we suggest before an activity that only works the recreational requirements.

- However, if we reach the current learner's *competence state* and no activities has been found for the selected competence, we choose another competence from the considered subset of competences, and we repeat the process.
- The strategy ends when the threshold is reached (in "Reinforcing") or when the maximum level of proficiency has been reached (in "Deepening"). Otherwise, both strategies can also end when all activities for the subset of competences have been done.

Next section presents a preliminary evaluation of the strategies in *Cristaux d'Éhère* (Cristaux d'Éhère, 2015), an SG for teaching physics.

4 PRELIMINARY EVALUATION

The different algorithms have been evaluated on the SG called *Cristaux d'Éhère,* designed to teach concepts related to physics consisting of 11 activities. The goal for each level is to solve problems about competences related to water state changes. Learners must move an avatar to interact with certain objects to reach a solution concerning physics-related topics.

A secondary education teacher, expert on physics, designed the domain model for the SG (see Figure 5). From this domain model (i.e. *precedence relations* between competences), we generated the *competence structure*.

The teacher also created the Q-Matrix (Tatsuoka, 1983); i.e. he linked the SG activities to the worked competences considering the tasks that can be performed in each activity (see Table 1). Besides, the different SG activities were linked to *competence state*s (the set of competences worked on in each activity forms the *competence state*).

Considering these information, we carried out an evaluation of the proposed strategies. Table 2 shows the obtained results. Expected results (used for validating the obtained results) are explained as follows:

- One possibility is to consider that the current *competence state* of the learner is the initial one. From the initial *competence state*, there is one next *competence state* that can be reached. The next *competence state* includes the competence '{h}'. Only the activity "*Act1*" is linked to this *competence state*. Therefore, if we apply the Advancing strategy and no previous activities have been done by the learner, the next suggested activity is "*Act1*". However, if "*Act1*" has been done, since there are not more activities for this *competence state*, the Advancing strategy has to look at a higher *competence state* (containing more competences). That means, this strategy will look at the *competence state* formed by the competences '{h, i}'. Activities associated to this *competence state*, and therefore, suggested by the strategy are "*Act8*" and "*Act9*".
- From the initial *competence state* we cannot apply Deepening nor Reinforcing strategies since no competences have been worked yet. Therefore, no activities can be suggested for this particular case.

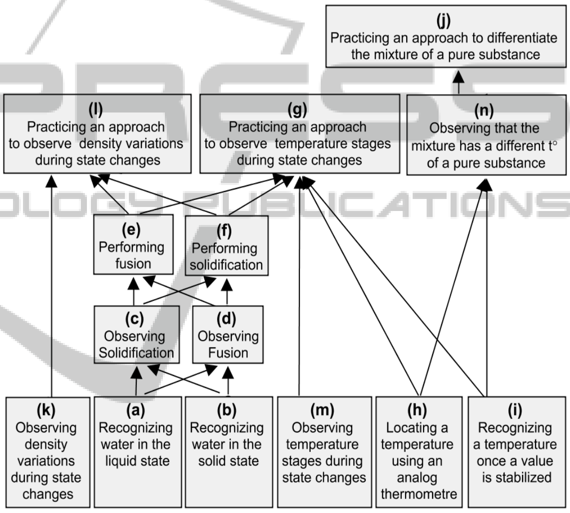

Figure 5: Domain model for *Cristaux d'Ehere*.

Table 1: Extract of the matrix representing activities indexation in *Cristaux d'Ehère*.

Activities	Competences								*Competence states*
	a	b	c	d	e	f	h	i	
Act1							x		{h}
Act2		x		x			x	x	{b,d,h,i}
Act3			x				x	x	{c,h,i}
Act4		x			x		x		{b,e,h}
Act5				x	x		x	x	{b,e,h,i}
Act6	x		x			x			{a,c,f}
Act7	x		x				x	x	{a,c,h,i}
Act8							x	x	{h,i}
Act9							x	x	{h,i}

- Another possibility is to consider that the current *competence state* of the learner is formed by competences '{h, i}'. If we apply the Advancing strategy, next *competence state* that can be reach

Table 2: Results obtained when applying the proposed strategies in *Cristaux d'Ehère*.

Current *competence state*	Subset of competences to train (if applicable)	Activities done	System confidence	Suggested activity		
				Advancing	Deeping	Reinforcing
Initial state =ø	-	None	-	*Act1*	None	None
Initial state =ø	-	*Act1*	-	*Act8*	None	None
{h, i}	"h" (Reinforcing) "i" (Deeening)	None	0.3 : "h" 0.7 : "i"	*Act3*	*Act9*	*Act1*
{h, i}	"h" (Reinforcing) "i" (Deepening)	*Act3*	0.3 : "h" 0.7 : "i"	*Act7*	*Act9*	*Act1*

contains the competences '{c, h, i}'. There is only one activity for this new *competence state* which is "*Act3*". Therefore, the Advancing strategy should suggest this activity. However, if this activity has been done by the learner, since there are no more activities for this *competence state*, the Advancing strategy has again to look at higher *competence states*. Then, possible activities to be suggested are: "*Act7*", "*Act5*", or "*Act2*".

- Furthermore, we can again consider that the current *competence state* of the learner is formed by competences '{h, i}'. For this *competence state* we can suppose that the system confidence for the first competence is 0.3, and for the second competence is 0.7. Then, if a teacher wants to apply the Deepening strategy to train the competence '{i}', expected activities to be suggested are: "*Act8*" or "*Act9*". These activities are those from the same and previous *competence states*.
- Similarly, if a teacher wants to apply the Reinforcing strategy to train the competence '{h}', expected activities to be suggested are: "*Act1*", "*Act8*" or "*Act9*". These activities are those from the same and previous *competence states*.

From an algorithmic point of view, we validated the results obtained by the strategies (see Table 2) compared with the expected results. Indeed, a co-designer involved in the implementation of the SG also validated the obtained results. These promising results lead us to consider a broad evaluation with other experts and SGs.

5 DISCUSSION AND FUTURE WORK

Current literature focuses on improving confidence values computed by systems in regards to the proficiency level of learners.

The innovative part of this work is: (a) to combine specific needs of teachers with the traditional approach (i.e. taking into account the current *competence state* of the learner); and (b) to implement this combination in adaptation strategies by using CbKST.

The adaptation strategies result from the needs expressed by teachers and companies involved in the project. The implementation of these strategies is based on different input parameters (mainly, subset of competences and threshold). We believe that the proposed approaches can be extended and applied to other pedagogical needs, as long as these needs can be translated into the concepts of CbKST (i.e. *competence state* and *competence structure*).

We have developed a tool that allows teachers to specify the different inputs required for adaptation strategies: subset of competences, threshold, sorting SG activities by level of difficulty. Currently, we are testing the implementation of these strategies in different SGs. Further work includes: (a) an evaluation comparing the results provided by the decision module to teachers' expectations; and (b) assessing learners by applying the proposed strategies and evaluating the impact on learners' performance.

Finally, other research line consists in using CbKST as an analytical method to identify gaps in the design of the SGs. Indeed, by using CbKST it is possible to identify *competence state*s for which there are no associated activities.

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