Adapting Learning Paths in Serious Games: An Approach Based on Teachers' Requirements

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Abstract. Adapting Learning Paths in Serious Games (SGs) is a challenging problem. Indeed, learners are not alike; they have different range of abilities, competences, needs and interests. A well-fitting approach to create adaptive SGs is based on Competence-based Knowledge Space Theory (CbKST). CbKST allows sequencing the SG activities according to knowledge and competences of a domain model, 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 consider implementing different adaptive approaches that fulfil their needs.

In this work, we propose to use CbKST 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 needs concerning the possibility of advancing forward learning paths of SGs, as well as of reinforcing and deepening learners' comprehension in specific subsets of competences. Therefore, we propose different recommendation strategies that allow teachers to modify the behaviour of adaptation in SGs, and we describe how we implemented and evaluated these strategies.

Keywords: Serious Games · Adaptation · Teacher's strategies · Competence-based Knowledge Space Theory

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 [1]. 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

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the complexity of the contained tasks [2]. As a consequence, learners become less frustrated and their motivation is increased [3].

Competence-based Knowledge Space Theory (CbKST) has been proven to be a well-fitting basis for realizing adaptation in SGs [4]. This methodology allows a non-invasive assessment of the learner without interrupting the game flow experience [5]. 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 [5,6]. 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 [1,7,8]. In other words, teachers' decisions could be based on the variety of teaching styles, learners' knowledge and performance, learning styles, and learning contexts [1,9].

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 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 Sect. 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 Sect. 3, we present the general architecture of the decision module. Particularly, we present the recommendation strategies considering the identified needs presented in the previous section. In Sect. 4, we describe the evaluation that has been carried out in order to compare between the system's results and the results obtained from teachers. Finally, in Sect. 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 [10]. 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:

– Authoring tools for supporting the development of SGs (e.g. SG scenarios).
– Monitoring tools for analyzing learning actions and assessing learners' competences.
– 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:

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.

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 on 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.

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 [11].

As representative works of curriculum sequencing environments we can cite the adaptive hypermedia [11] 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) [12]. 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) [6,13], as a potential framework for adapting learning paths in SGs.

2.2 Competence-based Knowledge Space Theory (CbKST)

CbKST is an extension of KST [12]. 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 [14]. 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 [4,5,15,16]. 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.

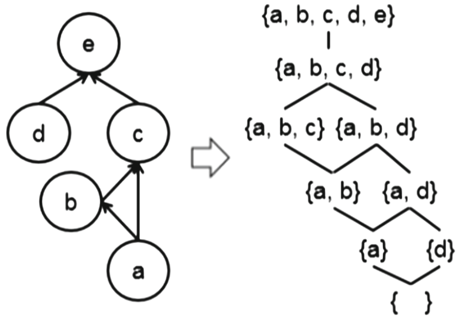


Fig. 1. Example of precedence relations (left graph) and competence structure (right graph).

3 Architecture of the Decision Module

We propose the development of a decision module based on an adaptation model proposed by Kopeinik et al. [5] in order to implement the different recommendation strategies. Like Kopeinik 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 Fig. 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. 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 Sect. 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 [17] 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 sections focus on describing the different modules of the decision module.

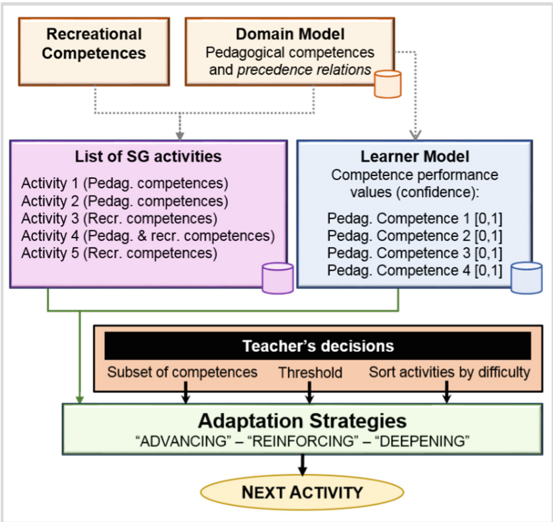


Fig. 2. Logic architecture of the decision module.

3.1 Domain Model

The XML schema of the domain model is depicted in Fig. 3. Each competence of the domain model is composed by the following attributes: "Id", "Name", and "Level". The different relations between competences are described in the "Link-list" element. Each "Link" is composed by the following attributes: (a) an id ("Id"); (b) a reference to the id of a source competence ("SourceId");

(c) a reference to the id of a target competence ("TargetId"); and (d) the type of relations (attribute "Name"), being "composition", "prerequisite" or "precedence" the possible values.

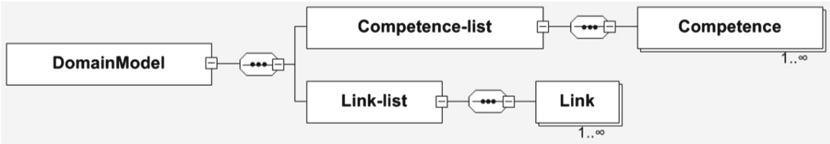


Fig. 3. Graphical representation of the domain model.

3.2 Learner Model

The learner model stores the information about the confidences associated to each competence of the domain model. This model also stores the information about the activities done by the learners. The information of the learner model (element "LearnerModel-Extended") is defined in a XML document compliant with the schema depicted in Fig. 4. The element "LearnerModel" contains the list of competences of the domain model. Each competence (element "Competence") contains the following attributes: a reference to the id of a competence defined in the domain model (attribute "Id"), a reference to the name of the competence ("Name"), and the confidence value for the competence ("Confidence"). The "LearnerModel-Extended" also stores the information about the list of activities performed by the learner (element "LearnerActivity"). Each activity done by the learner (element "Activity") contains the following attributes: "Id", "Name", and "Difficulty".

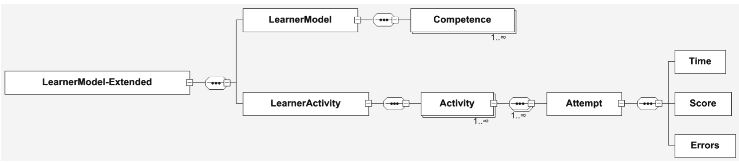


Fig. 4. Graphical representation of the learner model.

3.3 Recommendation Strategies

The recommendation module of the decision module implements three different strategies that depend on the purpose of the teacher. The strategies consider the competence structures based on CbKST (Sect. 2.2) for building the competence structure. In particular, these strategies are:

– The "Advancing" strategy that aims at working the maximum number of competences in a certain domain.

- The "Deepening" strategy that aims at providing the learner with activities to become expert in certain competences.
- The "Reinforcing" strategy that aims at providing the learner with activities to reinforce certain competences.

"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 Table 1, left).

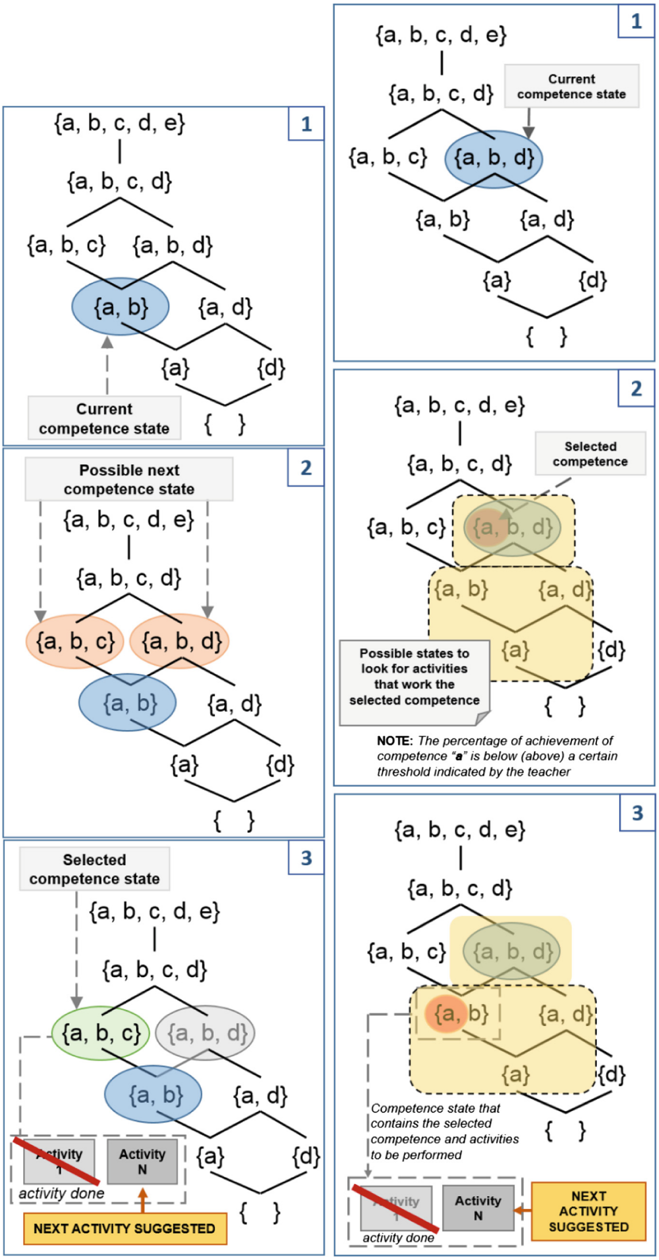
The next activity to be played is suggested as follows.

- 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 Table 1, left-1). 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 Table 1, left-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.

"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 Table 1, right-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 Table 1, right-2).

Table 1. Graphical example of the behaviour of the "Advancing" strategy (left). Graphical example of the behaviour of the "Deepening" and "Reinforcing" strategies (right).



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

– First, we get one competence from the subset of competences.
– 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 Table 1, right-2).
– Then, for each of these competence states we get the activities that have not been done yet (see Table 1, right-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 an evaluation of the strategies in "Les Cristaux d'Éhère" [18], an SG for teaching physics.

4 Evaluation

The different algorithms have been evaluated on the SG called "Les Cristaux d'Éhère", designed to teach concepts related to physics consisting of 18 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 Fig. 5). From this domain model (i.e. precedence relations between competences), we generated the competence structure.

The teacher also created the Q-Matrix [19]; i.e. he linked the SG activities to the worked competences considering the tasks that can be performed in each activity (see Fig. 6). Besides, the different SG activities were linked to competence states (the set of competences worked on in each activity forms the competence state).

Considering these information, an evaluation has been carried out considering the competence structure created from the domain model of "Les Cristaux d'Éhère". In particular, we compared the results obtained from the competence structure based on the domain model with answers provided by the secondary education teachers involved in the definition of the domain model.

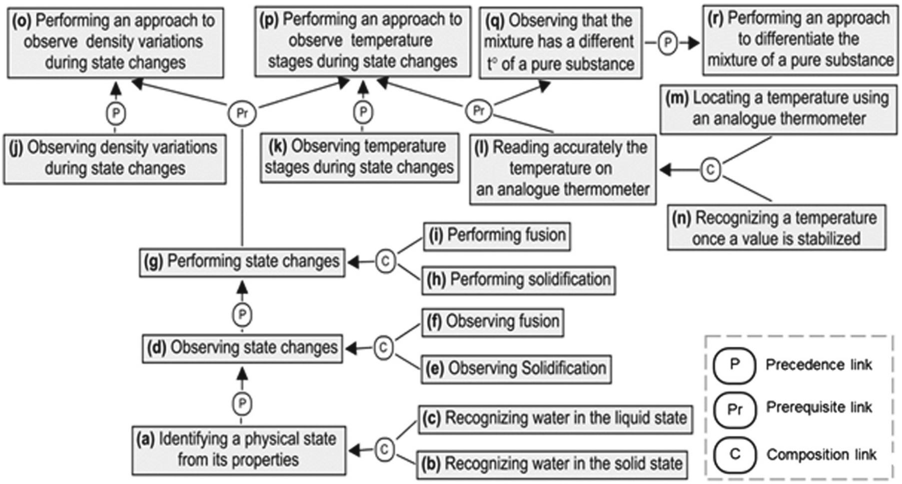


Fig. 5. Domain model for “Les Cristaux d’Éhère”.

4.1 Results Obtained from the Implemented Recommendation Strategies

We have specified different input parameters to evaluate the three implemented strategies. Concretely, we have defined seven tests with different CSs (Competence states) as starting point, as well as concrete set of competences and threshold values to be used by “Reinforcing” and “Deepening” strategies. Using this information, Fig. 7 shows the results of applying the adaptation strategies to the competence structure.

Furthermore, expected results can be inferred by looking at the competence structure that contains the SG activities and related CSs. Thus, these expected results (used for validating the obtained results shown in Fig. 7) are explained as follows:

– Test 1: The learner is in the initial CS and no previous activities has been done. In this case, it makes no sense to apply Reinforcing or Deepening strategies since no competences have been previously worked. However, if we apply Advancing strategy, we have to look at CSs that only contain one competence. Thus, the expected result is only the “Act1” that belong to the CS “[m]”.
– Test 2: The learner’s CS is “[m, n]” and no previous activities have been done. Besides, the system confidence for competence ‘m’ is 0.7, and for competence ‘n’ is 0.4. If we apply the different strategies the expected results are:
  • “Advancing” strategy: This strategy is expected to suggest activities from CSs “[b, f, m, n]” or “[b, e, m, n]” (i.e. successors of current CS that contain activities). This means, that potential activities to be suggested are “Act4” or “Act5”, respectively.
  • “Deepening” strategy for competence ‘m’ and a threshold value of 0.6: This strategy is expected to suggest an activity from previous CSs; i.e. from the initial CS to the current CS. That means, CS “[m]”, and therefore, “Act1”.

Activities	b	c	e	f	h	i	j	k	m	n	o	p	q	r	*Competence States (CSs)*
Act1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	{m}
Act2	0	0	0	0	0	0	0	0	1	0	0	0	1	1	{m, q, r}
Act3	0	0	1	1	0	0	0	0	1	1	0	1	0	0	{e, f, m, n, p}
Act4	1	0	0	1	0	0	0	0	1	1	0	0	0	0	{b, f, m, n}
Act5	1	0	1	0	0	0	0	0	1	1	0	0	0	0	{b, e, m, n}
Act6	1	1	0	1	0	1	0	1	1	0	0	0	0	0	{b, c, f, i, k, m}
Act7	1	1	0	1	0	1	0	1	1	1	0	0	0	0	{b, c, f, i, k, m, n}
Act8	0	1	1	0	1	0	1	1	0	0	0	0	0	0	{c, e, h, j, k}
Act9	0	1	1	1	1	1	0	0	1	1	0	0	1	0	{c, e, f, h, i, m, n, q}
Act10	0	0	0	0	0	0	0	0	1	1	0	0	0	0	{m, n}
Act11	0	0	0	0	0	0	0	0	1	1	0	0	0	0	{m, n}
Act12	1	1	1	1	1	1	0	1	1	1	0	1	1	0	{b, c, e, f, h, i, k, m, n, p, q}
Act13	1	1	1	1	1	1	1	1	1	1	0	1	1	0	{b, c, e, f, h, i, j, k, m, n, p, q}
Act14	1	1	1	1	1	1	1	0	1	1	0	0	1	1	{b, c, e, f, h, i, j, m, n, q, r}
Act15	1	1	1	1	1	1	0	1	1	1	0	0	1	1	{b, c, e, f, h, i, k, m, n, q, r}
Act16	1	1	0	0	1	1	0	1	1	1	0	0	1	1	{b, c, h, i, k, m, n, q, r}
Act17	1	1	1	1	1	1	0	1	1	1	0	1	1	0	{b, c, e, f, h, i, k, m, n, p, q}
Act18	0	0	0	0	1	1	1	0	1	1	1	0	0	0	{h, i, j, m, n, o}

Fig. 6. The Q-matrix representing activities indexation in "Les Cristaux d'Éhère".

  - "Reinforcing" strategy for competence 'n' and a threshold value of 0.4: Since there are not previous CSs with competence 'n' that contain activities, this strategy is expected to suggest an activity from CS "[m, n]", and therefore, "Act10" or "Act11".
- Test 3: Similar to Test 2, but in this case we consider that the learner has already done the activities "Act1" and "Act10". For this case, the expected results are:
  - "Advancing" strategy: Same expected result as in Test 2, since the activities done by the learner do not influence in next CSs. Thus, "Act4" or "Act5" are expected to be suggested.
  - "Deepening" strategy for competence 'm' and a threshold value of 0.6: Since "Act1" has been done and there are not more previous CSs with competence 'm' that contain activities, this strategy is expected to suggest an activity from CS "[m, n]". Besides since "Act10" is also done, the only expected activity to be suggested is "Act11".
  - "Reinforcing" strategy for competence 'n' and a threshold value of 0.4: Since there are not previous CSs with competence 'n' that contain activities, this strategy is expected to suggest an activity from CS "[m, n]". Besides since "Act10" is already done, the only expected activity to be suggested is "Act11".
- Test 4: The current learner's CS is "[b, e, m, n]" and no previous activities have been done. Besides, the system confidence for the different competences are: 'b' = 0.3, 'e' = 0.3, 'm' = 0.8, and 'n' = 0.4. If we apply the different strategies the expected results are:

  - Advancing strategy: Starting from "[b, e, m, n]", the first successors containing activities are "[b, c, e, f, h, i, j, m, n, q, r]" and "[b, c, e, f, h, i, k, m, n, q, r]". Therefore, "Act14" and "Act15" are expected to be suggested, respectively.
  - Deepening strategy for competence 'm' and a threshold value of 0.6: This strategy is expected to suggest an activity from previous CS "[m]", and therefore, "Act1".
  - Reinforcing strategy for competence 'b' and a threshold value of 0.4: There are not previous CSs with competence 'b' that contain activities. Then, this strategy is expected to suggest activities from CSs "[b, e, m, n]", and therefore "Act5".
- Test 5: Same as Test 4 but considering that the learner has already done the activities "Act1", "Act10", and "Act11". Then, the expected results are:
  - Advancing strategy: Same expected result as in Test 4, since the activities done by the learner do not influence in next CSs. Thus, "Act14" and "Act15" are expected to be suggested.
  - Deepening strategy for competence 'm' and a threshold value of 0.6: Since "Act1", "Act10", and "Act11" have been done, previous CSs "[m]" and "[m, n]" cannot be suggested. The only expected activity to be suggested is "Act5" from CS "[b, e, m, n]".
  - Reinforcing strategy for competence 'b' and a threshold value of 0.4: There are not previous CSs with competence 'b' that contain activities. Then, this strategy is expected to suggest activities from CSs "[b, e, m, n]", and therefore "Act5".
- Test 6: The learner's CS is "[b, c, e, f, h, i, k, m, n, q]" and no previous activities have been done. Besides, the system confidence for the different competences are: 'b' = 0.3, 'c' = 0.4, 'e' = 0.3, 'f' = 0.4, 'h' = 0.4, 'i' = 0.4, 'k' = 0.5, 'm' = 0.7, 'n' = 0.5, and 'q' = 0.8. If we apply the different strategies the expected results are:
  - Advancing strategy: This strategy will look at the direct highest CSs containing activities. From current CS, the direct highest CSs are "[b, c, e, f, h, i, k, m, n, q, r]" and "[b, c, e, f, h, i, k, m, n, p, q]". Thus, expected activity to be suggested are "Act12", "Act15", and "Act17".
  - Deepening strategy for competence 'm' or 'q' and a threshold value of 0.6: This strategy is expected to suggest activities from lowest-level previous CSs that contain 'm' or 'q'. Thus, expected activity is "Act1" from CS "[m]".
  - Reinforcing strategy for competence 'b' or 'e' and a threshold value of 0.4: This strategy is expected to suggest activities from lowest-level previous CSs that contain 'b' or 'e'. Thus, expected activity is "Act5" from CSs "[b, e, m, n]".
- Test 7: Same as Test 6 but considering that the learner has already done the activities "Act1", "Act2", "Act4", "Act5", "Act10", and "Act11". Following the same reasoning as in Test 6, expected activities are:
  - Advancing strategy: Same expected result as in Test 6, since the activities done by the learner do not influence in next CSs. Thus, "Act12", "Act15", and "Act17" are expected to be suggested.

Tests	Current CS	Subset of competences and threshold (if applicable)	Activities done	System confidence	Suggested activity		
					Using the competence structure built by the domain model		
					Advancing	Deepening	Reinforcing
Test 1	Initial state ∅	-	-	-	Act1	None	None
Test 2	[m, n]	[m] - 0.6 Deep. [n] - 0.4 Reinf.	-	[m] 0.7 [n] 0.4	Act5	Act1	Act10
Test 3	[m, n]	[m] - 0.6 Deep. [n] - 0.4 Reinf.	Act1 Act10	[m] 0.7 [n] 0.4	Act5	Act11	Act11
Test 4	[b, e, m, n]	[m] - 0.6 Deep. [b] - 0.4 Reinf.	-	[b] 0.3 [e] 0.3 [m] 0.8 [n] 0.4	Act14	Act1	Act5
Test 5	[b, e, m, n]	[m] - 0.6 Deep. [b] - 0.4 Reinf.	Act1 Act10 Act11	[b] 0.3 [e] 0.3 [m] 0.8 [n] 0.4	Act14	Act5	Act5
Test 6	[b, c, e, f, h, i, k, m, n, q]	[m,q] - 0.6 Deep. [b,e] - 0.4 Reinf.	-	[b] 0.3 [c] 0.4 [e] 0.3 [f] 0.4 [h] 0.4 [i] 0.4 [k] 0.5 [m] 0.7 [n] 0.5 [q] 0.8	Act15	Act1	Act5
Test 7	[b, c, e, f, h, i, k, m, n, q]	[m,q] - 0.6 Deep. [b,e] - 0.4 Reinf.	Act1 Act2 Act4 Act5 Act10 Act11	[b] 0.3 [c] 0.4 [e] 0.3 [f] 0.4 [h] 0.4 [i] 0.4 [k] 0.5 [m] 0.7 [n] 0.5 [q] 0.8	Act15	Act6	Act6

Fig. 7. Results obtained when applying the recommendation strategies to the competence structure built from the domain model of "Les Cristaux d'Éhère".

- Deepening strategy for competence 'm' or 'q' and a threshold value of 0.6: Since "Act1", "Act2", "Act4", "Act5", "Act10", and "Act11" have been done, previous CSs "[m]", "[m, q, r]", "[b, f, m, n]", "[b, e, m, n]" and "[m, n]" cannot be suggested. The only expected activity to be suggested is "Act6" from CS "[b, c, f, i, k, m]".
- Reinforcing strategy for competence 'b' or 'e' and a threshold value of 0.4: This strategy is expected to suggest activities from lowest-level previous CSs that contain 'b' or 'e'. CSs "[b, f, m, n]" and "[b, e, m, n]" cannot be suggested since activities "Act4" and "Act5" have been done. Thus, expected activity is "Act6" from CSs "[b, c, f, i, k, m]".

Next section describes an evaluation with the secondary teacher involved in the definition of the domain model and the Q-Matrix for "Les Cristaux d'Ehère". We propose the teacher to suggest activities based on the aforementioned tests. The comparison between the answers provided by the teachers and the obtained results from the strategies will provide insights on the relevance of the proposed approach.

4.2 Results Obtained from the Teacher's Answers

We carried out an evaluation with the secondary teacher involved in the definition of the domain model (Fig. 5) and the Q-Matrix (Fig. 6) for "Les Cristaux d'Ehère". We described the three adaptation strategies to the teacher. In order to not influence the teacher's answers, we did not explain the concepts related to CbKST; i.e. we did not explain that decisions on suggested activities are based on the competence structure. Then, we proposed the teacher to suggest activities based on the same situations (i.e. tests) as presented in Fig. 7. In order to gather his answers, we designed a questionnaire based on multiple-choice questions in which the teacher had to select the suggested activity (or activities) for each situation. In order to simplify the description of the different situations, we did not include the information about the system confidence. The confidence values are probabilistic numbers computed by the system, and therefore, this information is not relevant to be considered by the teacher. For instance, the description provided to the teacher for the situation of test 2 was: "Imagine a situation in which a student has played "Les Cristaux d'Ehère". Besides, the student has knowledge on: [m] Locating a temperature using an analogue thermometer, and [n] Recognizing a temperature once a value is stabilized. Considering this situation, you have to select the activity that you will suggest your student for: (1) advancing; (2) deepening in competence 'm'; and reinforcing competence 'n'".

Once the teacher filled the questionnaire, we compared his answers with the results obtained from the implemented recommendation strategies (described in Sect. 4.1). From this comparison, we notice that there were several cases in which the answers provided by the teacher (see Fig. 8) differ from the expected results.

Tests	Current CS	Subset of competences (if applicable)		Activities done	Suggested activity		
					Advancing	Deepening	Reinforcing
Test 1	Initial state ø	-		-	Act6 (*Case 1*)	-	-
Test 2	[m, n]	[m] [n]	Deepening Reinforcing	-	Act6 (*Case 2*)	Act10 (*Case 3*)	Act3 (*Case 4*)
Test 3	[m, n]	[m] [n]	Deepening Reinforcing	Act1, Act10	Act4 (*OK*)	Act9 (*Case 4*)	Act5 (*Case 4*)
Test 4	[b, e, m, n]	[m] [b]	Deepening Reinforcing	-	Act3 (*Case 2*)	Act10 (*Case 3*)	Act8 (*Case 6*)
Test 5	[b, e, m, n]	[m] [b]	Deepening Reinforcing	Act1, Act10 Act11	Act4 (*Case2*)	Act14 (*Case 4*)	Act18 (*Case6*)
Test 6	[b, c, e, f, h, i, k, m, n, q]	[m,q] [b,e]	Deepening Reinforcing	-	Act12 (*OK*)	Act2 (*Case 5*)	Act5 (*OK*)
Test 7	[b, c, e, f, h, i, k, m, n, q]	[m,q] [b,e]	Deepening Reinforcing	Act1, Act2, Act4, Act5, Act10, Act11	Act14 (*Case 2*)	Act17 (*Case 4*)	Act18 (*Case 6*)

Fig. 8. Results obtained from the teacher's answers.

In order to better understand the suggestions made by the teacher, we meet him and jointly compared and discussed the results. From the joint discussion with the teacher, six different cases were identified that explain the reasons because the teacher's answers were different from the expected results:

- Case 1: For the initial situation in which the learner is in the initial CS and no previous activities has been done, the "Advancing" strategy starts by looking at CSs that contain only one competence. If no activities are found, then the strategy advances forward in higher CSs. In this case the expected result is the "Act1" that belong to the CS "[m]". However the teacher suggested "Act6". The reason behind that is because this activity works competence 'i'. For the teacher, this competence is conceptually easier than competence 'm'. In fact, if we look at the domain model (see Fig. 5) competence 'i' has no precedence competences, while competence 'm' is preceded by other competences. However, the competence structure does not contain any activity for the CS "[i]". The suggestion from the strategy is correct but it is not what the teacher would select.
- Case 2: The "Advancing" strategy moves forward in the learning path by adding one competence to the current learner CS each time. Besides, the "Advancing" strategy only looks at CSs that can be reached from the different learning paths that belong the current CS. The teacher's decision for "Advancing" made sense since he considered the current learner's CS and proposed other activities with higher number of competences. However, considering the competence structure, the proposed activity selected by the teacher is not reachable from the current learner's CS. For instance, when applying the "Advancing" strategy to Test 2, the current CS is "[m, n]" and teacher suggested "Act6". This activity belongs to "[b, c, f, i, k, m]" which is not part of any of the learning paths from the current CS.
- Case 3: For "Deepening" strategy, we only look at the competence to work in depth. However, the teacher also took into account if the competence is part of a composition. In that case, given a competence, the teacher suggested activities that work on not only the intended competence but also all the competences that form the composition. As an example, in test 2, the "Deepening" strategy suggests "Act1" that belongs to the CS [m] for deepening 'm'. However, the teacher suggested "Act10" that belongs to the CS "[m, n]" for working in depth the competence 'm'. If we look at the domain model (see Fig. 5), competences 'm' and 'n' are composition of another competence (i.e. 'l').
- Case 4: "Reinforcing" and "Deepening" strategies consider the current learner's CS and looks at previous CSs to reinforce or work in depth concrete competences, respectively. However, the suggestions made by the teacher considered higher CSs from the current learner's CS. The reasons given by the teacher was: (a) for reinforcing, the teacher aimed to make the learner realise on his/her weaker competences by suggesting a more complex activity, and (b) for deepening, the teacher aimed to push the learner to become experts in concrete competences by working other several competences (i.e. challenging the learner to solve more complex activities). For instance, if learner is in CS [m, n] and we want to work in depth competence 'm', the strategy looks at previous CSs that work 'm', and therefore, the suggested activity could be "Act11". However, the teacher suggested "Act9" that work 'm' but also competences 'c', 'e', 'f', 'h', 'i', 'n', and 'q'.
- Case 5: From a subset of competences, "Deepening" strategy works on a competence each time. However, teacher considered that the subset of competences

has to be worked on at once. For instance, in test 6, the CS is "[b, c, e, f, h, i, k, m, n, q]" and we aimed to work in depth "[m, q]". The strategy suggested "Act1" that belongs to CS "[m]" while the teacher suggested Act2 that works both competences 'm' and 'n' (i.e. CS "[m, q, r]").
– Case 6: Some mismatches result from problems with the defined Q-Matrix. This issue is also the main reason of having activities that did not match to any of the CSs in the competence structure obtained from the domain model. We were interested in knowing whether the domain model designed by him might contain flaws or these mismatches come from the Q-Matrix. Therefore, the teacher paid attention to the "unconnected" activities by looking at their addressed competences and the domain model. Then, the teacher realised that there were some problems in the Q-Matrix; he missed to relate some of the competences to few activities.

5 Discussion and Future Work

Currently, adaptation is based on improving confidence values computed by systems in regards to the proficiency level of learners. The innovative part of our work is the combination of specific needs expressed by teachers with this traditional approach (i.e. taking into account the current competence state of the learner). This combination has resulted in the successful implementation of a decision module and an authoring tool for adapting learning paths in SGs.

The decision module is based on CbKST and implements three adaptation strategies that address specific teachers' requirements. The adaptation strategies result from the needs expressed by teachers and companies involved in the Play Serious 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).

Currently, we are testing the implementation of these strategies in different SGs. This research work has also identified several future research lines:

– assessing learners by applying the proposed strategies and evaluating the impact on learners' performance,
– supporting teachers in defining the granularity level of competences to define domain models that can be readable and manageable by teachers and computationally built by systems.
– 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 states for which there are no associated activities.

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