Increasing Learners' Motivation through Pedagogical Agents: The Cast of Virtual Characters in the DynaLearn ILE

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Abstract. Motivation is a critical requirement for successful learning. Previous research has identified that animated pedagogical agents can increase motivation. Following these results, we present the cast of pedagogical agents in the DynaLearn Intelligent Learning Environment. Each of these agents is associated with one of the different support types available in the environment, giving each agent a clearly defined role. We describe the different character roles, how their knowledge is generated and related to the pedagogical purpose at hand, how they interact with the learners and finally how this interaction helps increasing the learners' motivation. To assess this, we conducted a preliminary evaluation with three of the characters and report our findings.

Keywords: Pedagogical Agents, Virtual Characters, Intelligent Learning Environments, Motivation, Engagement.

1 Introduction

Embodied conversational agents are widely used in virtual learning and training environments [1,2,3]. Beside possible negative effects of virtual characters [4], there is evidence that virtual pedagogical agents and learning companions can increase the learners' commitment to the virtual learning experience [5,6]. They can promote the learners' motivation and self-confidence, help to prevent or overcome negative affective states and minimize undesirable associations with the learning task, such as frustration, boredom or fear of failure.

It has been shown that a one-sided coverage of knowledge transfer or the employment of only a single educational role may either lead to satisfying learning success or motivation, but usually not both at the same time [7]. The usage of multiple virtual characters with different but complementing roles can have positive influence on both the learners' learning success and their engagement. Teams

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of pedagogical agents can help the learners to better understand the conveyed knowledge [8].

The context of our research is *DynaLearn* [9], an intelligent learning environment (ILE) in which learners learn by expressing their conceptual knowledge through qualitative reasoning models [10]. In this paper, we present DynaLearn's cast of pedagogical agents that were added to the ILE, the educational principles they are built upon and how they interact with each other and the learner. The goal of our research is to increase learners' motivation and learning success when using the learning environment.

The remainder of this paper contains related work (Section 2), a section on the different characters (3), the overall architecture of the system (4), the evaluation we conducted (5) and a critical reflection of our work as well as an outlook (6).

2 Related Work

Kim and Baylor [7,11] reported in their work on virtual learning companions three different aspects like competence, activity and realism. As we did in the DynaLearn project, they adopted human metaphors in their visual designs and focused especially on the three qualities competency, activity and realism. The competency assigned to a virtual character depends for example on the role the character takes. For example instructor-like expertise might weaken the peer-likeness which works against being helpful or motivating. Their experiments show that a high competence avatar decreases self-efficacy belief in tasks but leads to good learning effects and recall-results. Low competence on the other hand may increase self-esteem, confidence and the learner's sense of responsibility, but can be useful for introducing novices to learning and to motivate to explore further fields of the learning objectives. Further research showed that people attribute human properties to computers each time they are using them. Virtual characters may utilize this phenomenon for naturally engagements by adapting and simulating human like behaviors. Nevertheless it was found that too realistic designs leads to unrealistic expectations and therefore to disappointed or irritated feelings for the user. Consequently virtual characters experience a higher acceptance if the user's expectations for the creature's behavior meet the actual experience.

The classical role of an agent in a learning environment is that of a teacher, see for example [12] and [1]. "AutoTutor" [13] allows learners to learn facts from a given domain by having a natural language conversation with a talking head, the virtual tutor. These dialogs are very interactive since both the learner and the virtual tutor work together to improve the learner's answer.

"Betty's Brain" [14] features the virtual character Betty (realized as a talking head) who is a so-called teachable agent. As the name implies, learners can teach Betty by building a concept map (i.e. her brain) and asking questions about it. The goal for the learner is to prepare Betty for a quiz about a given domain. Blair et al. also suggest to have multiple teachable agents compete against each other in a quiz show like application. Questions are asked by a virtual quizmaster and each agent responds according to their concept map.

In [15] another virtual character is mentioned that was added to "Betty's Brain": Mr. Davis, the teacher (also realized as a talking head). Mr. Davis helps the learner to teach Betty by giving guidelines about teaching in general or hints that address specific situations that learners might find themselves in. Since these hints are directed at the learner, there is no real interaction between Mr. Davis and Betty. Moreover, his hints only refer to teaching, not the task or domain at hand.

A closer look at these interactive learning environments shows that all three feature a teacher-like character that interacts with the learner to help or teach. However, how this interaction looks like and what is actually communicated differs widely: One of the systems follows the Learning by Teaching paradigm by introducing a character that is taught by the learner. One system features fully embodied agents, that can also communicate through gestures. Finally, one of the systems features more than one virtual character or rather more than one character role. However, as stated above, these characters only interact with the learner and not with each other.

We hypothesize that a combination of these features, implemented in an integrated set of educational characters may better leverage learning. Hence, in the DynaLearn approach we decided to integrate the following character roles into our learning environment: A *Teacher* who answers specific questions and offers help about the learning environment itself. A *Mechanic* that analyzes a learner's model and offers a diagnosis through an interactive dialog. A *Teachable Agent* who can be taught by the learner. A *Critic* who gives quality feedback and finally a *Quizmaster* who adds a playful and competitive element by asking the learner questions, but who also directly interacts with the teachable agent to form a presentation team as suggested in [8]. Before we start with describing each of the characters in detail in the next section, Figure 1 gives an overview by showing each of the characters with a typical line of dialog with regard to the model depicted in the center.

3 The Characters in DynaLearn

As we delineated in [16], the characters in DynaLearn are cartoonish hamsters. Also, we employ three established teaching methods: *Learning by Teaching* [15], *Scaffolding* [17] and *Educational Quizzes* [18]. The design of our character interactions also incorporates some of the different dialog modes (such as lecture or highlighting) identified for expert tutors by Cade et. al in [19].

During learners' interaction with the software, all virtual characters are available all the time and it is up to the learners which one to consult, depending on the desired type of support. Learners can interact with the characters in two different ways: Buttons above the characters' heads (for starting specific kinds of interactions) and multiple-choice selections in the characters' speech bubbles (for answers and follow-up questions). Figure 2 shows four examples of these interaction possibilities.

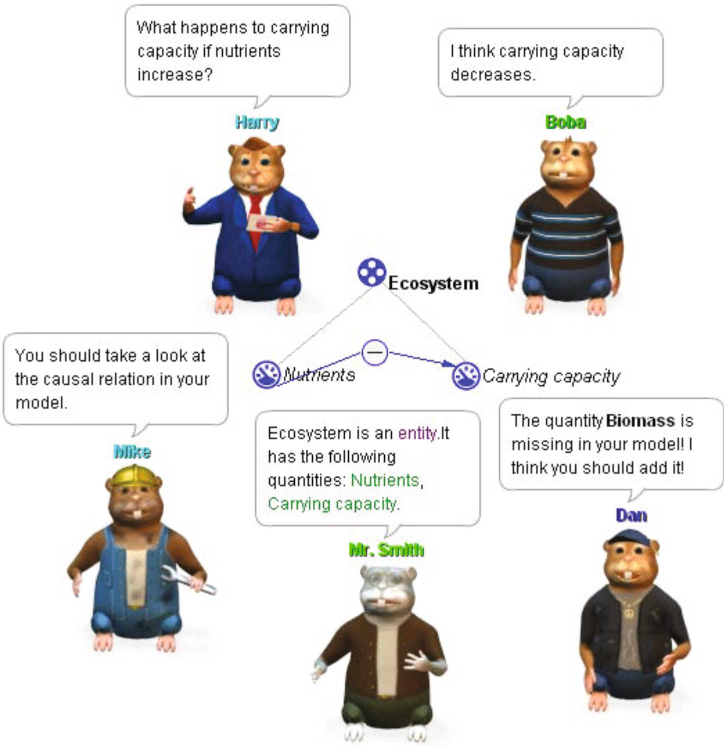

Fig. 1. The DynaLearn Characters (clockwise from top left): Quizmaster, Teachable Agent, Critic, Teacher, Mechanic

3.1 Teachable Agent (TA)

The DynaLearn TA brings the Learning by Teaching paradigm into the ILE. The TA has a knowledge representation that can be created by the learner. From this structured knowledge the TA can extract answers to questions asked by the learner. The TA is also able to explain its reasoning, so the learner can see how causal chains arise in his own model. By testing the TA's understanding of the matter through questioning, the learner can evaluate his own presentation of the knowledge and detect mistakes when the TA does not answer as expected. In DynaLearn, learners can chose between a male and a female TA and also name it. Similar to "Betty's Brain", the interactions learners can perform with their TA are: Ask (TA answers single questions), Explain (TA provides a step-by-step explanation of an answer) and Challenge (TA takes a quiz).

Constant verification of the own understanding is an important part in the learning process that unfortunately often comes short due to the learners' aversion to tests. However, learners are less restrained in confronting an agent several times with the same test than in retaking this test themselves. That's why we allow the learner in our application to take part in a quiz and to send his

Fig. 2. Examples of interaction possibilities with the characters (from left to right): Mechanic offering different ways to proceed, interactions with Teachable Agent trough buttons, multiple-choice answer to question asked by the Quizmaster, hyperlinks in Teacher's answer for follow-up questions

personal teachable agent to this quiz in his place. Since the TA's knowledge mirrors an image of the learner's knowledge, he may serve as a proxy in an educational quiz. We will discuss this learning scenario later in section 3.4.

Though Learning by Teaching aims for learning success the role of the teachable agent is more a motivating one. Following the research of Kim et al. [7] our TA forges a more peer-like relationship to the learner with his low-competent behavior. For example some dialog contents convey an insecure personality of the agent to emphasize his dependence on the learner. There are also dialog parts in which the agent takes a moment to think about a question (either asked by the learner or the quizmaster) so the agent does not seem smarter as the human learner who also needs some time to think in such situations.

3.2 Mechanic

The task of the mechanic is to support learners in analyzing their model. Oftentimes, the simulations results of the model the learner created are not in line with the learner's expected outcome. An automated diagnostic component (based on [20]) detects these discrepancies, and identifies a minimum number of model components that caused this discrepancy. The mechanic is used to communicate these diagnosis results. The learner can then engage with the mechanic character in several ways: First, the learner can alter the model components that the character has suggested and then rerun the simulation to see whether the outcome is now satisfactory. Alternatively, the learner can reaffirm that the model is actually correct, in which case the mechanic points out that under those conditions the fault must be in the learner's expectation regarding the simulation results.

We chose the constructivist approach of Scaffolding as learning principle for this role. Scaffolding emphasizes that the learner should do as much work by himself as possible. The teacher or tutor only provides assistance if the learner does not possess the necessary skills or knowledge to solve the current problem on his own. According to [21], this helps the learner to become more and more independently. While this describes the effect of scaffolding in the long run, in short-term it aims for maximum learning success by keeping the learner motivated and ensuring he makes constant progress in his work.

The work of Lipscomb et al. [17] , Larkin [22] and Cade et al. helped us identify the means for reaching this goal. While Cade et al. mention scaffolding as one of their mutual exclusive dialog modes in one-on-one tutoring sessions, Lipscomb et al. and Larkin describe scaffolding as a more extensive teaching principle. We incorporated both ideas in our mechanic role. The more widespread scaffolding of Lipscomb et al. determines the general behavior of our mechanic, while we use some of the dialog modes of Cade et al. as dialog steps within this behavior.

The aids used by the mechanic during this process are assigned to one of the following three categories: Lecture, Scaffolding, Modeling. These categories are similar to the dialog modes described by Cade et al., although their mode of Highlighting is part of our Scaffolding aid. The agent usually chooses with an equal chance between lecture and scaffolding when providing an aid. These chances are again based on the observations of Cade et al. where lectures and scaffolding were the most present dialog modes with a very similar frequency. As we ideally want the learner to find the solution by himself modeling, the exact correction of the mistake, is only appropriate if the mechanic has exhausted all other means. In this way, we ensure the learner can proceed with the correction of his model even if he can not cope with a particular problem.

3.3 Teacher

In contrast to the mechanic, the teacher offers a more direct kind of help by communicating knowledge pertaining to those aspects of the ILE that are visible to learners and that they can directly interact with. There are three kinds of such directly visible aspects, and each is covered by a different kind of help: Firstly, there is the diagrammatic representation of the learner-created model, consisting of the various modeling ingredients. With respect to any one of these, a “What is X?”-question can be posed. Secondly, there is the visualization of the behavior of the model. This consists of a manifold of changes (each with a cause) in values. With respect to each value a “Why was X derived?”-question can be asked. Thirdly, there are the screens, dialogs and buttons that constitute the interface of the software. A menu of “How to X?”-questions is constantly generated (where X is a task), based on the tasks that are available given the learner-created model and the state of the software. The answers that the teacher character communicates are concise and focused with respect to individual knowledge requests. If the learner wants to know more, the help message contains hyperlinks that pose follow-up questions that allow the exploration of related material. In addition, a glossary of important terms is provided. Whenever a virtual character mentions one of these glossary terms, they are also displayed as hyperlinks. The descriptions in the glossary are interlinked, amounting to a traversable graph of explanatory messages.

3.4 Quizmaster

The quizmaster may be employed in a quiz directly with the human learner or with the learner's TA. The entertaining performance of quizmaster and TA helps to point out flaws and verifies the correct parts of the learner's model. The question generator for the quizmaster is based on the QUAGS question generator [23]. The generation of questions is domain independent and done in four steps: First the given restrictions are analyzed with respect to the simulation and completed with built-in heuristics. Then the resulting criteria lead to the generation of a set of question designs based on the simulation input and a set of templates. Thirdly a selection inference determines the best set of questions given the full set of successful designs. Fourthly this final set of questions is put in a logical order with groups of questions for every state in the simulation.

Knowledge tests are usually perceived as stressful situations having negative effects on concentration or motivation. In observations of quiz forms in several well known television quiz shows we found out that quizmasters sometimes try to loosen up such situations in order to countervail their negative effects and to provide an enjoyable form of test. For that purpose, they start lively conversations with their candidates and discuss topics that are familiar to the participants such as job or leisure activities. We mimic this behavior with our quizmaster character. Beside the quizmaster's general behavior of asking questions and giving feedback, we integrate smalltalk utterances into the dialog. They serve as short, preferable humorous distraction for the participant that actually need no connection to the current topic of the quiz and its questions.

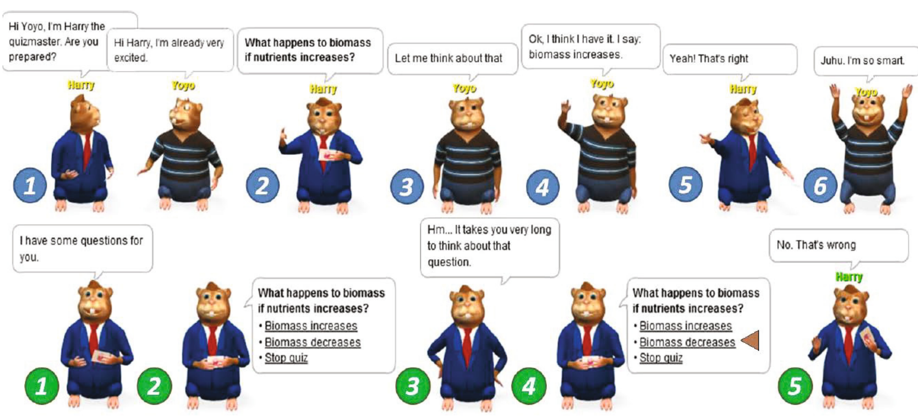

Fig. 3. Different ways of running the quiz: Quizmaster and TA (top), Quizmaster and learner (bottom)

As mentioned in section 3.1 the quizmaster may be employed in a quiz with the human learner or with the learner's teachable agent. The entertaining performance of quizmaster and teachable agents helps to point out flaws in the learner's model and verifies the correct parts of the learner's model. Usually the latter should be the case if the learner follows the suggested order, which means the educational quiz comes after the correction of the model in the instructional scaffolding phase. But this order is not obligatory since the learner can activate the agents whenever he wants. The quiz with the teachable agent as participant might also be used as a test of the model and taken again after the correction phase as a knowledge verification.

Figure 3 shows both ways the quizmaster can be employed: With a learner's TA or directly with a learner.

3.5 Critic

In contrast to the content delivered by the mechanic or teacher characters, the critic's quality feedback about a learner's model is generated through the *semantic repository* in the DynaLearn software. Also, while the others are friendly and helpful, the critic is characterized as more strict and unforgiving. The semantic repository of DynaLearn is intended to store the models created by the users and to provide feedback during the model creation process [24]. These models are semantically grounded, so the terms of the model are linked to semantic descriptions in a common vocabulary (which in our system is DBpedia [25]). The quality feedback is the result of comparing the learner's model with a reference model by using techniques like ontology matching [26], semantic reasoning, and QR specific comparisons between the models.

If two terms are grounded to the same semantic description we infer that they are equivalent terms, even if they are expressed using different lexical information or even in different languages. Then, the set of equivalent terms is enhanced by applying ontology matching techniques. The next step is to analyze each pair of equivalent terms looking for possible differences. These provide the following types of feedback: i)Improvement of terminology (suggest label of reference term if different from current label), ii)Missing and extra ontological elements (point out terms only present in one of the two models), iii)Inconsistencies between hierarchies (point out inconsistencies in entity hierarchies found through semantic reasoning) and iv)Differences between the structures (point put differences in model structure).

4 Architecture

The overall architecture of the Virtual Character Component (VC) and its connection to the Conceptual Modeling Component (CM) can be seen in Figure 4. In DynaLearn, the CM is where learners actually build their models and where the various kinds of conceptual knowledge are generated.

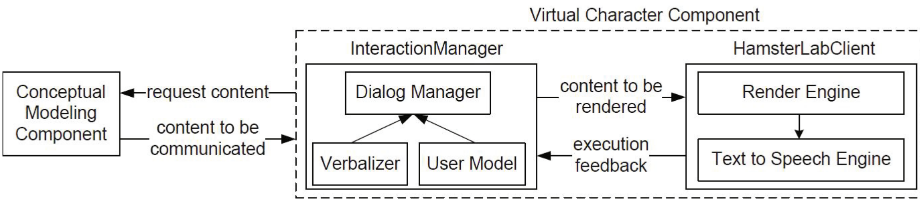

Fig. 4. The Virtual Character Component Architecture

The VC in itself consists of two different components, the InteractionManager (IM) and the HamsterLabClient (HL). The HL is responsible for actually displaying the virtual characters which is handled by a Flash-based render engine. Also, the HL generates the characters' speech using the Mary Text-to-Speech System [27]. The IM's main responsibility is to create the characters' behavior by requesting appropriate content from the CM, arrange it into dialogs between the different characters and create the appropriate scene script that can then be played by the HL. Scene scripts are XML-based and consist of different instructions such as "move", "say" or "animate". A feedback channel informs the IM when a scene script is over. The IM itself consists of three different modules:

– The Dialog Manager governs the overall interaction between the characters and the learner. When necessary, it requests new data from the CM and then decides "What to say". In our implementation, we use SceneMaker [28] as the Dialog Manager.
– The Verbalizer decides "How to say it", i.e. what words to use.
– The User Model keeps track of the learner's knowledge and interactions. The data provided by it can act as a filter or decision criteria for the Dialog Manager.

We will now take a closer look at how these modules interact with each other when creating a dialog for the characters. Figure 5 shows an overview of this process.

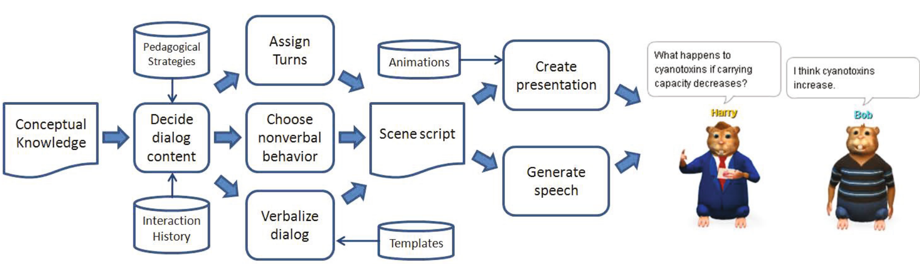

Fig. 5. Character Dialog Generation Process

The process starts with the input from the CM, i.e. a certain kind of conceptual knowledge. As an example let us assume that a learner just sent his TA to take a quiz. As a result the conceptual knowledge submitted in this case will be questions generated by the system, answers to these questions generated from the learner-created-model and finally the correct answers. First the dialog content needs to be decided. This can be based on previous actions by the learner (derived from the User Model) or the characters, as well as certain pedagogical strategies.

Next, the content needs to be assigned to the different characters. In our example, the quizmaster character will ask the questions and present the correct answers, while the TA will present the answers generated by the learner-created-model. Also, the quizmaster will comment on the TA's success and the TA will show a reaction to that.

After that, the dialog turns are verbalized using a collection of templates that are filled in with the appropriate data. If there is more than one matching template, one of them is chosen randomly. For example, the same question could be verbalized as "What happens to cyanotoxins if carrying capacity decreases?" or "Let's suppose carrying capacity decreases, what would then happen to cyanotoxins?", depending on the template selected.

Finally, nonverbal behavior is selected to accompany the dialogs. The characters can move around the screen, perform gestures and facial animations and point out spaces on the screen. In our example, after each question the quizmaster will perform either a thumbs-up gesture or shake his head depending on the TA's success, and the TA will perform a cheering or sulking gesture accordingly.

Based on the decisions made, the scene script XML can then be constructed and sent to the HL. Then, the content of "say"-tags is extracted and the speech is created accordingly. Together with the appropriate data from the animation library, the dialog can finally be presented by the render engine.

5 Evaluation

We conducted an evaluation to investigate the learners' attitude towards and interactions with three of the characters (teacher, quizmaster, teachable agent) and the employed learning principles (instructional scaffolding, learning by teaching, educational quiz). In addition, we compared the learners' level of engagement when they participated in a quiz as opposed to sending their TA. It should be noted that the interaction with the teacher was based on a mock-up version rather than a fully functional one.

5.1 Method

We recruited 20 subjects (10 male and 10 female, aged between 25 and 33, mostly computer scientists) who interacted with the three characters in the following situations: First, the subjects had a look at a faulty model and could ask the teacher for help in order to correct the model. After that, they participated in a quiz where they had to answer questions posed by the quizmaster. Finally, the subjects were requested to train their own TA and test its performance in another quiz with the quizmaster. Since it did not make sense to confront the subjects with the TA before they got acquainted with the learning scenario, we decided not to present the subjects with the single characters in a randomized order, but in a didactically appropriate one. Each subject's interaction with the characters lasted 30 minutes, 10 for each of the three situations. After each interaction with a character, subjects were asked to fill in a questionnaire, judging features of the interaction on a 5-point Likert scale (1 to 5, where 5 meant full agreement).

5.2 Results

Attitude towards the Different Agents and the Educational Setting. Overall, the subjects considered the agents' behaviors as quite natural. A t-test for one sample revealed that the ratings given to the agents were significantly above the neutral value of 3.0. The learners rated the naturalness of the teacher with a mean value of 3.65 ($t(19)=2.459$, $p \leq 0.03$), the naturalness of the quizmaster with a mean value of 4.2 ($t(19)=8.718$, $p \leq 0.001$) and the naturalness of the TA with a mean value of 4.0 ($t(19)=6.164$, $p \leq 0.001$). Furthermore, we were interested in the question of whether the agents' role was properly conveyed. Our subjects attributed to the teacher the highest level of competence with a mean value of 4.45 followed by the quizmaster with a mean value of 3.70. The teachable agent was attributed the least level of competence with a mean value of 3.25. Applying the Bonferroni post hoc test showed that the differences between TA and teacher ($p \leq 0.001$), as well as teacher and quizmaster ($p \leq 0.05$) were significant.

We also investigated the motivational effect of the agent roles. The learners found the interaction with the teacher less enjoyable with a mean value of 3.55 than the interaction with the TA with a mean value of 4.15 and the interaction with the quizmaster with a mean value of 4.3. Employing the Bonferroni post hoc test showed that the difference between the ratings for teacher and TA were significant ($p \leq 0.04$).

Furthermore, we investigated whether the learners thought the employed learning principle contributed to their learning process. The subjects found the teacher helpful with a mean value of 4.30 ($t(19)=8.850$, $p \leq 0.001$), they had the feeling that the quiz contributed to their understanding with a mean value of 4.60 ($t(19)=11.961$, $p \leq 0.001$) and they thought that they learned something themselves by teaching their own agent with a mean value of 4.20 ($t(19)=6.0$, $p\leq 0.001$). In all cases, the mean values were significantly above the neutral value of 3.0. In addition, the learners thought it made sense to employ a virtual teacher with a mean value of 3.7 ($t(19)=2.774$, $p \leq 0.02$), to employ a quizmaster with a mean value of 4.65 ($t(19)=15.079$, $p \leq 0.001$) and to employ a teachable agent with a mean value of 4.05 ($t(19)=4.098$, $p \leq 0.001$).

Finally, we evaluated whether the learners understood the employed metaphor when interacting with each character. In particular, we were interested in the question of whether the learners would be able to see the connection between the creation of a model and instructing an agent. We applied t-tests for one sample to evaluate whether the ratings given by the learners were significantly above the neutral value of 3.0. The learners had the feeling to ask a teacher a question with a mean value of 3.7 ($t(19)=2.774$, $p \leq 0.02$), to participate in a quiz with a mean value of 4.65 ($t(19)=15.079$, $p \leq 0.001$) and to teach somebody with a mean value of 4.25 ($t(19)=5.0$, $p \leq 0.001$). The results are shown in Figure 6.

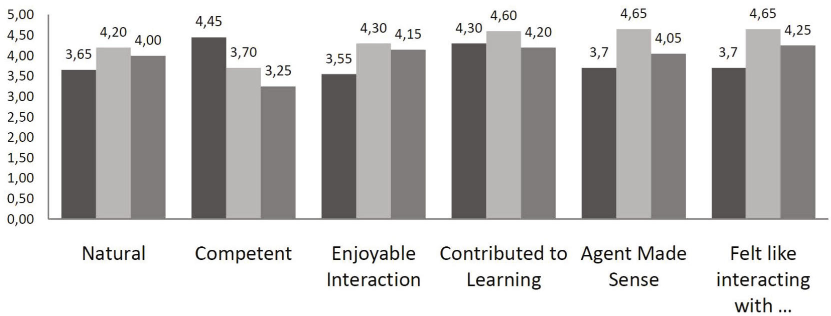

Fig. 6. Attitude towards the different agents and the educational setting

Comparison of Direct and Indirect Participation. We also compared the two versions of the educational quiz, i.e. learner as participant vs. TA as participant. The learners showed more engagement when their TA participated in the quiz than when participating themselves. In particular, they were more interested in a good performance with a mean value of 4.25 as opposed to a mean value of 3.85, more pleased about a good performance with a mean value of 4.55 as opposed to a mean value of 4.15 and more curious about the results with a mean value of 4.20 as opposed to a mean value of 3.60. However, the difference was not significant. The difference between the averaged ratings for the engagement items was weakly significant ($t(38)=-1936$, $p \leq 0.061$) with mean values of 3.86 for participating themselves and 4.33 for participating via the agent. An overview of the results is given in Figure 7.

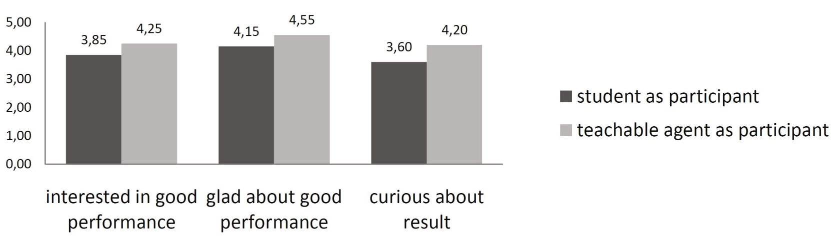

Fig. 7. Learner as quiz participant vs. TA as quiz participant

6 Conclusion

In this document, we presented our approach to a cast of pedagogical agents, whose interaction with the learner offer a variety of services that help learners to verify and correct their models and conceptual knowledge, while motivating and engaging them at the same time. We showed how presenting different kinds of knowledge through different character roles and teams of characters can result in an improvement in the use of virtual characters in ILEs. We also explained how our approach to the virtual characters' architecture supports this as it allows us transform conceptual knowledge into multimodal dialog scripts for multiple characters. We believe that our approach of an entire cast of pedagogical agents is a viable option for ILEs that aim at conveying knowledge trough multiple means: First, because each of these means can be linked to and associated with a specific character for easier identification. Second, because providing characters of different competence levels will positively affect both learners motivation and learning success.

To a certain degree, this was confirmed by the findings of our preliminary evaluation: Learners enjoyed the interaction with our pedagogical agents and perceived the virtual classroom setting as engaging and motivating. They understood the employed metaphor with its different learning scenarios and the justification of each of the three characters. They felt that the pedagogical agents, respectively their educational roles successfully helped learning.

However, since this is only a subjective measure of learning success, we plan to conduct further evaluations with regard to this topic. Other pointers to future work include evaluations of all character roles and learners' attitude towards them, as well as a measuring learners' motivation and engagement while interacting with the characters.

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