Teachable Agents with Intrinsic Motivation

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Abstract. Dynamic communication between Teachable Agents (TA) and students is crucial for educational effectiveness of the TA, as dynamic interaction is the vital part throughout the teaching and learning processes. Existing TA design mainly focuses on the functions and features to ensure the TA to be taught by students rather than bi-directional interaction. However, according to reciprocity theory in social psychology, if the TA can offer friendly actions, students in response will be much more cooperative and motivated. In order to improve quality of communication and seize the interest of students, we propose a need modeling approach to enable TAs to have "intrinsic motivations". In this way, the TA can proactively carry out dynamic communication with students so that the TA can adapt to students' changing behaviors and sustain a good human-agent relationship. Our field study showed that students were highly attracted by the TA with dynamic needs. They statistically completed more tasks. Also, better results were obtained on students' learning efficiency and attitude towards TA's informational usefulness and affective interactions.

Keywords: Teachable Agent · Intrinsic motivation · Dynamic communication

1 Introduction

Teachable Agent (TA) is a type of computer agent which is designed to be taught by students. According to Learning-by-Teaching Theory, the bi-directional interaction between TA and students can induce students to take the learning responsibility and achieve better learning outcomes [1]. The communication quality of TAs influences the educational value of the entire learning system [2], since students need to be convinced that their teaching is important and valuable for the "naïve" TA. Without effective interactions, a TA cannot persuade students to teach it even if the TA has the best student model and teaching knowledge. Moreover, according to reciprocity theory in social psychology, if the TA can offer friendly actions, students in response will be much more cooperative and motivated. Therefore, TA should spontaneously take actions and proactively interact with students to enlighten students' deep learning through teaching the TA.

To pursue agent's proactivity, we look into the field of Intrinsically Motivated Agent (IMA). IMA are based on the concept of "intrinsic motivation" from psychology. An agent is considered as intrinsically motivated when its behavior is "for its own sake", other than driven by an external stimulus [3]. If a TA could have intrinsic motivation, it

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can be designed to proactively interact with students by means such as asking questions related to students prior problems, asking for further explanation, looking into something new, etc. In light of this idea, our group has proposed the Intrinsically Motivated Teachable Agent (IMTA) in [4], which is motivated by psychological needs defined in Self-Determination Theory (SDT) [5]. SDT stated that three psychological needs elicit intrinsically motivated behaviors, namely Competence, Relatedness, and Autonomy. Actions are generated in order to avoid any dissatisfaction of these three innate needs. IMTA is designed to associate the innate needs with TA's educational requirements to facilitate students' learning experience.

Despite the proactive interaction and more interesting learning scenario provided by IMTA, the system design lacks a crucial part, the dynamic matching between IMTA's needs and motivated behaviors. As a result, the IMTA lacks of dynamic changes and generates monotonic reactions. In order to solve this problem and improve the quality of communication between IMTA and students, we aim to propose a new approach to model TA's psychological needs, and integrate the proposed need model into a real IMTA system. With the new model, the TA in our system can generate dynamic interactions with students and seize their attention throughout the learning process. To sum up, the objectives of this paper include: 1) model IMTA's needs and integrating into a TA-enhanced virtual learning environment; 2) evaluate students' interest in learning, learning efficiency, and attitude towards the refined IMTA.

In the following section, we will introduce the educational project where IMTA is embedded in, and discuss why a psychological need model is important. We propose the need model in Section 3, and report the field study results in Section 4. After the discussion on the experiment results, we end the paper in Section 5 with conclusions and future work.

2 Virtual Singapura Project and Related Work

An E-learning project, Virtual Singapura (VS), is applied to demonstrate the use of improved IMTA in practice. The VS platform is a 3D virtual learning environment, which allows secondary school students in Singapore to learn science lessons (especially the knowledge about the transport in living things). Two types of teachable agents "Little Water Molecules" and "Little Mineral Salt Molecules" were developed in the project, as in Fig.1a. VS project brings students to a journey together with water molecules to explore the inside of a running down banana tree (Fig. 1b), and to find out the problems. Students can teach the TAs through Concept Map panel (Fig. 1c) and experiment panels (Fig. 1d).

To improve the learning experience of students, TAs should adapt to students' dynamic behaviors and establish human-like interactions. Some researchers have worked in this area. For instance, Matsuda et al. [6] studied how to implement adaptive help of TA to facilitate student's learning. Biswas et al. [7] discussed the interactive action patterns with agent responses. Roger et al. [8] studied how to design dynamic prompting and feedback to improve students' learning efficiency. James et al. [9] investigated the relationship between dialogue responsiveness and learning with TA. These studies focus on how to appropriately design TA's responses to student, but they did not highlight the importance of TA's proactiveness. In this paper, the proposed IMTA are expected to spontaneously take actions and proactively interact with students, driven by its intrinsic motivation.

(a) (b) (c) (d)

Fig. 1. (a) Water and menarial salt molecules in underground. (b) 3D example demostration of sick banana tree. (c) Draw concept map in teaching panel by drag and drop. (d) teaching panel 2 expriments.

How to bring agents with intrinsic motivation? Several researchers from computer agents discussed their opinions: (1) Singh, from an evolutionary perspective, considered "reproductive success" as the drive for agents to behave proactively [10]; (2) Baranès & Oudeyer designed robots to pursue activities for which "learning progress is maximal" [11]; (3) Merrick considered agent's self-motivated exploration as seeking for "novelty, interest, and competence" [12]. Although the focus of exploration and learning new knowledge are paramount to motivated agents, they did not discuss how to design the intrinsic motivation for educational agents to improve students' learning. Thus, the proposed IMTA focuses on combining the motivation design with the pedagogical requirements and synthesizes the various behaviors into a unified sense of "self-willing", which may improve TA's dynamic interaction with students and enhance the believability.

3 Need Modelling in IMTA

This section discusses an improved system design incorporating a model of psychological needs and details of the model used in IMTA. To incorporate the educational requirements into TA's intrinsic motivation, we have designed three types of need of the proposed IMTA. The *Need of Novelty* let TA learn new knowledge from students, which provide opportunity for students to reflect on their knowledge; the *Need of Performance* let TA practice the learnt knowledge in learning environment, which help students to examine their teaching effect by observing TA's behaviors; the *Need of Relatedness* let TA keep tight relationship with students and more effectively attract students to perform as a good teacher. In our previous research, we have developed the mapping among ability of TA, needs of TA, and motivation of TA based on SDT. The mapping is given in Table 1 below, and this mapping continues to hold in this paper.

Table 1. Mapping among Ability, Needs, and Motivation of IMTA [2]

Ability	Need	Motivation
Teachability	Need of novelty	Pursuit of new knowledge
Practicability	Need of performance	Pursuit of performance
Affectivability	Need of relatedness	Pursuit of relatedness

In order to incorporate a model of psychological need and reflect the relationship between psychological needs and motivation, the architecture of IMTA is given in Figure 1 below.

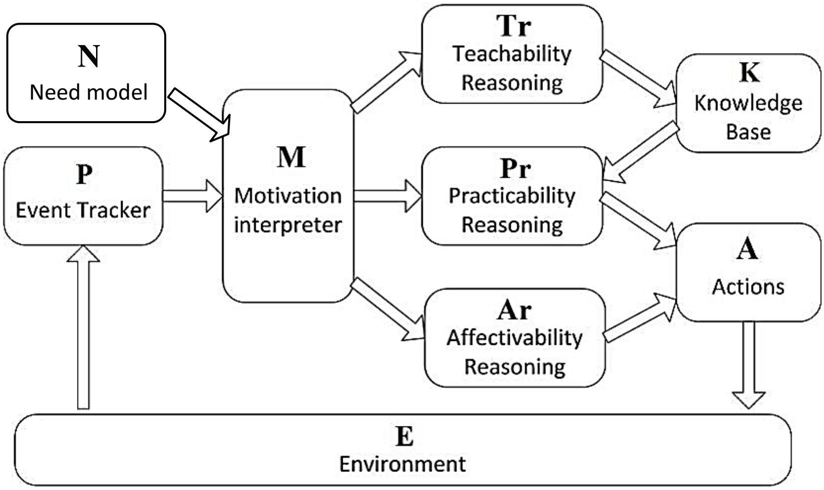

Fig. 2. IMTA's Architecture

In this architecture, Tr, Pr, Ar are the three reasoning entity that achieves teachability, practicability, and affectivability. M, Motivation Interpreter, provides motivation so that agent knows which goal to pursue. The most significant improvement is the introduction of N, need model, as another input to motivation interpreter in additional to event tracker. It simulates the real-life scenario where individual's motivation is affected not only by external stimuli in environment, but also by internal psychological needs. By linking output of need model to motivation interpreter, this architecture of IMTA resembles more closely to real-life learning behaviors.

In discussion below, the need model will be firstly introduced, followed by the model interpretation which uses need model as input to select motivation. Finally, a way to model the effect of past events on current need is discussed.

3.1 Intrinsic Need Functions

IMTA's different needs are modelled as different innate functions. Different needs have different relationships between need strength and time. At any given time, an IMTA may be challenged by the combination of different needs with different levels of activation.

An impulse signaling is used for generating peeks of needs across times. The impulse represents the internal tendency towards the pursuit of a need. Three impulse frequencies, $freq_{lo}$, $freq_{me}$, $freq_{hi}$, are used. In this paper, pursuit of performance is assigned with the highest frequency to stimulate the process adopted by the IMTA to reinforce concepts with students; pursuit of relatedness is with lowest to reduce non-necessary communication cost. Other agent designers can assign frequencies differently to reflect their own use case.

However, needs vary across time more closely to waves rather than impulses. Therefore, a set of smooth functions is further proposed to simulate need changes over time. The set of soft-windowing functions is defined as Equation (1) below.

$$\begin{gathered}
\mathrm{Duration}_i = {}^{1}\!/_{freq_i} \\
\mathrm{Win}_i = (t, t + \mathrm{Duration}_i) \\
\mu_i = {}^{1}\!/_{2}\ \mathrm{Duration}_i \\
\sigma_i = \frac{1}{factor_i}\mathrm{Duration}_i \\
\mathrm{WinFun}_i(t) = \exp\left(-\frac{(t-\mu_i)^2}{2\sigma_i}\right).
\end{gathered} \tag{1}$$

where t is the current time; i ∈ {"low", "mediate", "high"} denotes each of the three different need frequencies; Win_i refers to window i spanning from t (impulse firing time) to t + $Duration_i$; $Duration_i$ is the time span of window i; μ_i and σ_i are the center and spread of the i^{th} windowing function respectively; $factor_i$ is a predefined constant; and $WinFun_i$ is the Gaussian membership function defining the i^{th} window.

Equation (1) above is used in functions that describe need of novelty and need of performance. Need of relatedness does not fit Equation (1) because relatedness is less frequently needed, but once it emerges, the need function should excite itself immediately. This does not correspond to the smooth tails on both sides of Equation (1). To model the rapid emergence of need of relatedness, a Rayleigh distribution is used as below in Equation (2).

$$\text{WinFun}_i(t, \varsigma) = \frac{t}{\varsigma^2} e^{-t^2/2\varsigma^2}. \tag{2}$$

From definition of Rayleigh distribution,

$$\mu_i = \varsigma\sqrt{\frac{\pi}{2}} \approx 1.253\varsigma$$
$$\sigma = \frac{4-\pi}{2}\varsigma^2 \approx 0.429\varsigma^2 \tag{3}$$

An illustration of need functions is shown in Fig 3. The horizontal axis is time, and the vertical axis is need level. Three need functions are represented in Figure 2. Curve A represents need modelled by Rayleigh distribution; curve B and curve C represent needs modelled by Gaussian distribution.

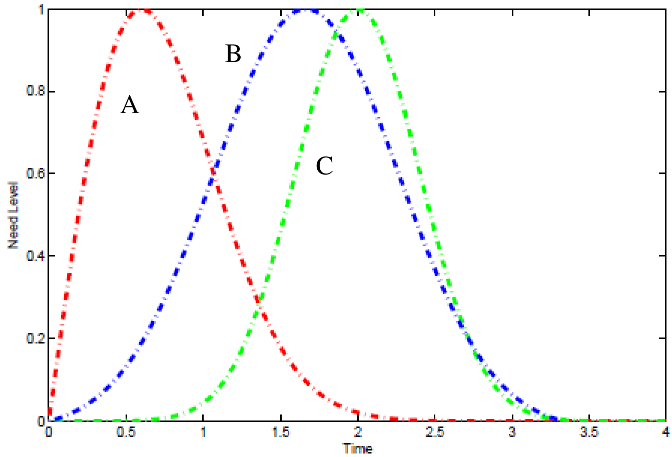

Fig. 3. Representation of Need Functions in Equation (1) and (2)

3.2 Motivation Interpretation

Based on SDT and our model, motivation arises because of intrinsic needs and external stimuli from environment. Motivation Interpreter is the entity that synthesizes information from external environment and intrinsic need to dynamically determine IMTA's current motivation. It takes values of intrinsic need functions discussed above to calculate motivation intensities. Intensity of motivation represents IMTA's eagerness to pursue that motivation. Different weights are also assigned to intrinsic need functions to represent the relationship between needs and motivations. In our model, IMTA's motivation intensity is calculated as follows:

$$V^{M_i} = w_i \times V^{N_i}, \forall i. \tag{4}$$

Where w_i denotes the need weight of need N_i, and V denotes the intensity of motivation and level of need.

IMTA will then proactively select motivation with highest intensity and tries to accomplish it by triggering one of the reasoning entities, Tr, Ar, or Pr. Each of the entities will have a set of well-defined goals. Once the goal can be achieved by IMTA given the stimuli from external environment, the motivation will be accomplished. The selection of current motivation resembles trade-offs in real life.

3.3 Weight Adjustment in Motivation Interpretation

In real-life learning, current learning need and target are also affected by what happened in the past. For example, if need of performance is not satisfied previously, the eagerness to satisfy this need will increase. IMTA's behavior should also be affected by outcome of past event. In this paper, the effect of past events on IMTA's needs is modelled by a simple weight adjustment in Equation (5) below,

$$w_i = w_i + \beta^n - \beta^p \tag{5}$$

where w_i denotes the need weight of need N_i, β denotes an updating rate in range (0, 1], and n or p denotes the number of times that the need is satisfied negatively or positively. Weights are always normalized to be bound within range [0, 1].

Using Equation (5), needs that are not previously satisfied will have higher weight in subsequent valuation, and motivations that can satisfy this need will be more likely to be selected. The needs that are satisfied previously will be less prominent in the next round of motivation interpretation.

4 Field Study and Results

The study was conducted in Xinmin Secondary School, Singapore. It aimed to examine if TAs with and without dynamic needs pursue may have different impact on students' learning. It was designed as "intervention versus ablated intervention" [2].

Students are randomly selected from the same grade. All students had not been taught about the subject and therefore deemed to have the same level of knowledge on the subject. They were divided into two groups; the treatment group consisting of 14 students used IMTA with intrinsic need model, while the control group consisting of 11 students used IMTA without intrinsic need model. The tests were deployed during student's Co-curricular Activities. Students were required to teach the IMTA in VS virtual environment on how water molecules and mineral molecules are transported from the root to the leaves, and among parts of the plant. There were 5 teaching tasks in 5 game scenes within the 3D sick banana tree, which are 1) Root, 2) Stem, 3) Xylem, 4) Leaf, and 5) Phloem. VS system automatically collected the number of tasks completed by each student and the time student spent in each scene. At the end of the study, the communication effectiveness of IMTA was measured by a questionnaire derived from the Agent Persona Instrument (API). It provides a holistic approach that takes into account different perspectives such as look and behavior, as well as computer-based aspects of the agent [13]. API includes 4 sub-measures – 1) facilitating learning, 2) credible, 3) human-like, and 4) engaging. The questionnaires were in 5-point scale, from 1 (strongly disagree) to 5 (strongly agree).

To sum up, we compare the treatment group and control group through:

(i) The number of teaching tasks students completed: to depict students' willingness to interact with TA. In our experiment, it was not compulsory for students to complete all tasks. Students could stop whenever they felt bored.

(ii) The average time spent of students in each teaching task: to indicate the learning efficiency of students

(iii) The questionnaire scores on students' judgments about the communication effectiveness of TAs

4.1 Number of Tasks Completion

Through analyzing students' data collected by TA system, we found that students in treatment group completed 3.57 tasks on average, and students in control group completed 2.58 tasks on average. We did a t-test and there was a significant difference of the tasks completed by two groups of students ($p = 0.02$). In order to find the cause of the difference, we did short interviews among the two groups of students. We found that students felt fun when TA's behaviors are less predictable. This made students in treatment group continue playing with the TA and see what the TA will perform next. We can conclude that students were motivated by IMTA with dynamic behaviors. They are interested in IMTA, and would like to teach IMTA more topics.

4.2 Average Time Spent on Each Task

There is also a significant difference ($p = 0.06$) in average time spent by student in each task. In treatment group, each student spent 346 seconds in one scene on average, while students in control group spent 624 seconds in one scene on average. This means IMTA with intrinsic need can increase learning efficiency. The improvement may derive from two perspectives. First, the generation of TA's needs, especially the need of novelty may easily cover all the knowledge points and quickly find students' problems. This can increase the learning speed of students. Second, according to students' feedback through the interview, they "want to teach more" so that they "planed the time to finish all the tasks" in their Co-Curricular Activities lessons.

4.3 Students' Attitude Towards IMTA

Students' attitudes towards the communication effectiveness of TAs further confirmed our analysis above. The IMTA with need model were better received by students. The differences in the self-report questionnaire results between two groups are summarized in table below. Each value pair follows Mean/Variance format.

Students in treatment group reported significantly better results in all of the four areas related to informational usefulness and emotive interaction. We can also find that the scores of Credible, Human-like, and Engaging in control group are much lower than the scores in treatment group. This may because that the dynamic need changes affect much more on TA's "personality" related factors, which make it more believable and interesting. Thus, the latter three factors improved much more on the

IMTA with need model. On the other side, the factor Facilitate Learning of IMTA without need model reached 3.15, which has the smallest differences from the IMTA with need model. This may be indicated that students still think the IMTA without need model is useful although it is not very interesting. Therefore, based on our study, IMTA with intrinsic needs model did interact with students more effectively, and stimulate student's learning interests.

Table 2. Comparison of Student's Attitude towards IMTA

Perspective	**Factors**	**IMTA with Need Model**	**IMTA without Need Model**	$P_{one\text{-}tail}$
Informational	Facilitate Learning	3.66/0.244	3.15/0.191	0.006
Usefulness	Credible	3.63/0.308	2.33/0.739	6.22E-5
Affective	Human-like	3.84/0.275	2.74/0.506	6.39E-5
Interaction	Engaging	3.43/0.371	2.82/0.160	0.004

There is also a quite interesting phenomenon that, for the IMTA without need model, we received lower scores from the self-reported questionnaires from secondary school students comparing with the results we collected in primary school grade four [2]. Though the survey questions are not exactly the same, there are still several similar questions in common. In our opinions, this may be because the students in secondary school are teenagers who are more critical. Their standards of a good educational game become higher than the younger ones. Therefore, our suggestion on this situation is that we can use 7 or 9 point scales rather than 5 point scales to collect more precise results from secondary students. Nevertheless, we will not compare the students from different age range.

5 Conclusion and Future Work

In this paper, we proposed a psychological need modeling approach to enhance the dynamic interactions of TAs with intrinsic motivations. The model has been used in VS, a 3D virtual learning environment. The TA in VS can proactively carry out dynamic communication with students so that it may adapt to students' changing behaviors. Positive results have been collected from the field study in secondary school. First, students in treatment group statistically completed more tasks than control group. Second, better results were obtained on students' learning efficiency in treatment group. Third, students reported higher scores towards TA's informational usefulness and affective interactions. Therefore, we conclude that the proposed model has been better received in communication with students and also enhanced students' learning experience.

There are also limitations of this study. First, the student sample size is limited. In the future we will conduct studies with larger data size so the statistical results will be more significant. Second, we have collected some but not rich enough behavioral data of students in the 3D learning environment. Those students' behavioral data may reveal much more first-hand student information and improve the analysis towards students' experience and preferences. Therefore, we plan to incorporate new functions into the existing system to record all types of user behavior data in the virtual learning environment. The data will then be analyzed to assess students' learning competencies, such as self-regulation, learning motivation, reflective thinking skills, etc.

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