< Modeling Study for Developing Motivational and Cognitive Adaptive Agent >

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ABSTRACT

Recent development of teachable agent provides learners with active roles as knowledge constructors and focuses on the individualization. The aim of this adaptive agent is not only to maximize the learner's cognitive functions but also to enhance the interests and motivation to learn. In order to establish the relationships among user characteristics and response patterns and to extract the algorithm among variables, we measured the individual characteristics and analyzed logs of the teachable agent named KORI (KORea university Intelligent agent) through the student modeling. A correlation analysis was conducted to identify the relationships among individual characteristics, user responses, and learning outcomes. Among hundreds of possible relationships between numerous variables in three dimensions, nine key user responses were extracted, which were highly correlated with either individual characteristics and learning outcomes. The results suggest that certain type of learner responses or the combination of the responses would be useful indices to predict the learners' individual characteristics and ongoing learning outcome. This study proposed a new type of dynamic assessment for individual differences and ongoing cognitive/motivational learning outcomes through the computation of responses without measuring them directly. The construction of individualized student model based on the ongoing response pattern of the user that are highly correlated with the individual differences and learning outcome may be the useful methodology to understand the learner's dynamic change during learning.

Keywords: Adaptive Agent, Student Modeling, Motivation, Cognition, Dynamic Measuring

INTRODUCTION

One-on-one instruction is a long ideal in educational research. It is because that kind of environment has been expected to offer individual learners adaptive instruction (Blatchford et al., 2005). In this respect, Intelligent Tutoring System (ITS) aroused researchers' interest in the field of education because it could solve the problems of one-on-one instruction in the school environment like limitation of time, space, and money. Researchers expected if ITS becomes popular, individual learners may receive expert-tutor-like assistances by ITS. However, there are frequent occasions when the effectiveness of ITS is below expectation. It is mainly because learners tended to show shallow learning related to solve the test questions in ITS rather than deep learning. As learners get passive roles in ITS, their motivation to learn is decreased and it cannot elicit active cognitive process of learners.

To solve these kind of problems, many researchers have tried to find solutions. One way is to give them tutor roles. The researchers in the field of cognitive science and learning science suggest that teaching activity facilitates to enhance learners motivation. For example, Kim et al. (2003) found that motivation can be attained by allowing learners to tutor roles which give responsibility, feeling of engagement, and situational interest to persist in learning. These motivated learners could be involved deeper in sub-activities of teaching such as memory and comprehension, knowledge reorganization, explanation, demonstration, questioning, answering, evaluation, and so on. It enabled learners to reach elaboration, organization, inference, and metacognition (Bargh & Schul, 1980). Biswas, Schwatrz, Bransford, and TAG-V (2001) developed the new concept of intelligent agent called Teachable Agent (TA) based on this learning by teaching paradigm. TA provides student tutors with tutor roles using ITS so that they can have active attitude toward subject matters like peer tutoring.

To enhance the effectiveness of TA, adaptive response of agent is one of the most important key factors. For improving this individualized adaptivity, it is necessary to assess learner's specific characteristics and dynamic changes of the learners' cognitive and motivational states using ITS. Thus, the system developers need to use a new methodology to get the learner responses and infer each learner's individual characteristics and the current motivational and cognitive state based on the analysis of indirect measurement like user's behavior logs. That is why modeling study is important.

As seen in Figure 1, three types of research should be integrated to develop the adaptive TA. As the first step of developing adaptive teachable agent, a student model was proposed based on the correlation among three dimensions: individual differences, learner responses, and learning outcome in this study. We tried to find the relationship between existing self-report questionnaire and leaners' on-going logs. Four variables of individual difference in metacognition and motivation were selected because differences in the level or type of motivation result in huge differences in persistence and efforts in learning (Pintrich & Schunk, 1996). Among various motivational factors, self-efficacy, learning and performance goal orientations were used in this study. Metacognitive awareness including planning, monitoring, and evaluation was measured since elementary school students may lack of this skill though it is a critical factor for their future learning.

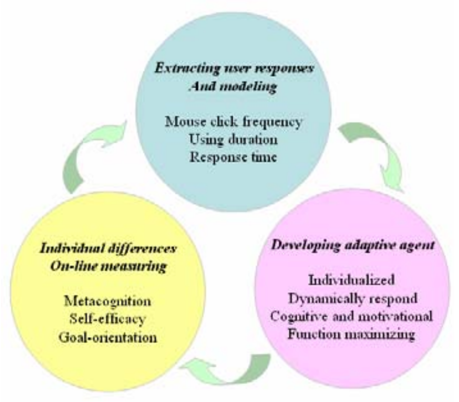

Figure 1: Relation between Student Modeling and Agent Development

METHOD

Participants

Twelve fifth graders (8 males and 4 females) participated in student modeling.

Teachable Agent (KORI)

KORI (KORea university Intelligent agent) is a new type of teachable agent that is developed to enhance learners' motivation to learn and facilitate learning. It was made by JAVA Swing and Jgraph components and implemented based on JAVA platform.

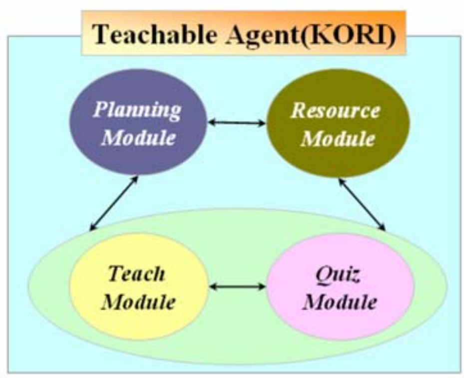

Figure 2: Teachable Agent (KORI) modules

KORI consists of four independent modules: planning module, teaching module, learning resource module, and quiz module. Figure 2 shows the relationship of each module. In the planning module, users make the specific plan for teaching KORI and collect and sort the learning materials to teach from learning resources. There are four empty boxes to type their own teaching plan on three kinds of rocks and their transformation cycle. This module would have the user realize the role of a tutor, get involved in teaching situation deeply, and have more responsibility. Previous researches reported that the tutors got more cognitive benefits than tutees (e.g., Bargh & Schul, 1980). It is important to make users believe to be real tutors. This module is expected to assess users' metacognitive ability by examining the quality of the lesson plan and planning duration.

In the teaching module, users teach KORI by providing the basic characteristics of various rocks and constructing concept map on the transformation of the rocks. The basic concepts were described in the form of simple propositions. The concept map is a kind of relational diagram that represents relationships among the concepts in learning materials (Novak, 1996). This expresses the hierarchies or causal relationships of knowledge (Stoyanov & Kommers, 1999).

The teaching module consists of two activities: concept teaching and transformation teaching. In the concept teaching activity, users teach the basic concepts of three kinds of rocks: igneous rock, sedimentary rock, and metamorphic rock. They teach KORI by putting in five correct propositions and taking out five incorrect propositions among 15 given propositions. After teaching the basic concepts, users teach the transformation process of rocks by drawing a concept map (see Figure 3.). To teach KORI, users should understand and remember the basic concepts of each rock and recognize the relationships and transformation among rocks.

Figure 3 shows relation teaching interface of KORI. Users can put the concepts whatever he/she want and draw arrows between concepts to indicate their relations. In the main window of the screen, users put the name of rock in the box and make a transformation relation between rocks with the arrow. The process of transformation is represented by mathematical symbol. Plus symbol (+) means increase of the weathering factors while minus symbol (-) means decrease. Below the concept mapping window, there is dialogue box that users can interact with KORI. There are four taps, each of which has a different function, including KORI's talk to facilitate the perceived interactivity, KORI's interpretation of the concept or relation, learning resource, and KORI's quiz score and automatic feedback on KORI's performance by the system.

The learning resource module provides basic and expanded knowledge about rocks and their transformation. Users can access to this module by clicking the icon whenever they want to know more about rocks while teaching KORI. The resource is made of hypertext that is linked the basic concepts to concrete images and examples. There are two different levels of learning resource: basic learning resource and additional learning resource. The basic learning resource is the minimum amount of knowledge that is essential to teach KORI. Additional learning resource is the expanded knowledge that is not directly related to teach KORI. It is expected that the durations and frequencies of exploring both levels of learning resource would be correlated with individual characteristics or motivation.

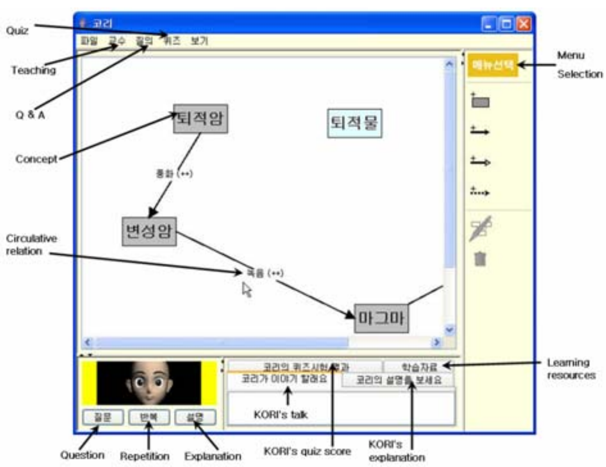

Figure 3: Relation teaching interface of KORI

In the quiz module, KORI takes a quiz at the end of teaching. The quiz consists of 6 questions of rocks.

Although KORI seems to take the quiz, in fact, it evaluates users' level of the knowledge and comprehension. Since KORI's answers for the quiz are based on the information taught by users, KORI's achievement level means the cognitive learning outcome of users. While KORI is taking the quiz, the user is asked to choose one of three activities: the review of the rock taught to KORI just before, taking the quiz together, and the preview of other rocks. These activities are intended to provide another opportunity to explore the learning materials in different way.

During exploring four modules of KORI, diverse choice situations are given to increase learner controllability and to promote the learning motivation: whether competing with another KORI or not, whether getting additional information or not, whether monitoring KORI's cognitive and emotional state or not, and selecting the difficulty level of teaching. For example, before the concept teaching, the user is asked to estimate the KORI's quiz score at the end of teaching and the difficulty level of teaching. In addition, while teaching KORI, the user can give his/her own feedback to KORI through a dialogue box depending on the unexpected KORI behavior, which is predetermined, such as falling into a doze during learning. The increased self-determination of the user would enhance their autonomy and self-relevance to the learning material, which would result in more engagement in teaching KORI with more enthusiasm.

Procedure

Participants took 30 minutes lesson on 'rock cycle' together to acquire the base knowledge in the domain. Since 'rock cycle' is the content for seventh graders, it was revised to be suitable for fifth graders. After the lesson, participants filled in questionnaires on self-efficacy, goal-orientation, and metacognition. Then, each participant's behaviors based on the structured checklist and videotaped the scene of teaching KORI. The log data of each participant's responses were recorded automatically through the computer during the interaction with the KORI. It took approximately 30 - 40 minutes to complete teaching KORI. After teaching KORI, participants completed the interest and comprehension questionnaires. And while watching the video of their own behaviors, they were given a structured interview on the reason for each response and their emotional and motivational reaction at particular point of time.

NODE AND STRUCTURE IN STUDENT MODEL

A correlation analysis among the log data, questionnaire scores, and learning measurements was conducted. We delineated the relationship among three dimensions, learner responses (mouse-click pattern, duration & frequency at particular task, individual choice etc), individual characteristics (metacognitive awareness, self-efficacy, learning goal, and performance goal), and learning outcomes (interest and comprehension) during KORI teaching.

Among hundreds of possible relationships between numerous variables in three dimensions, the relationships of which correlation coefficient was higher than .3 were included in the student model. This cutoff standard point was set moderately high level from all of correlation relationships among hundreds of variables. In the student model, the nodes represent variables in each dimension and the arrows represent the relationships among nodes (see Figure 3). The nodes and structure of the student model showed (ⅰ) the overall relationship between individual characteristics and participants' responses, (ⅱ) the specific relationships between participants' responses and learning outcomes. These results suggest that certain type of learner responses or the combination of the responses would be useful indices to predict the learners' individual characteristics and ongoing learning outcome. Each dimension in the student model was described in detail in the following section.

Learner responses

The log data included about 150 learner responses. Among those, eleven key learner responses were extracted based on the correlation coefficient (cutoff r = .3) between individual characteristics and learner responses, and between learning outcomes and learner responses. Eleven key learner responses were the duration and frequency of exploring the learning resource, the difference between and the actual science test score of the learner and the predicted score of KORI, the latency for performance estimation, the duration and frequency of concept and concept map teaching, and the number of correct concept selection.

Learning resource (d) Learning Resource (d) is the durations of exploring the resources for 'rock cycle'. The resources are directly related to basic concepts to teach KORI as putting in the correct propositions and taking out the incorrect propositions among 15 propositions.

Learning resource (f) Learning Resource (f) is the frequency of exploring the resources of 'rock cycle'.

Estimation (d) Estimation (d) is the durations of estimation of performance that KORI would get at the end of the teaching. We expected this estimation duration might be index of participant's metacognitive ability.

Estimation (s) Estimation (s) is the score of the estimated KORI's performance. This also was expected participant's individual difference metacognitive ability.

Difference between estimation and performance Difference between performance and estimation is the differences between each learner's actual science test score and predicted score of KORI ay the end of the teaching.

Planning Time (d) Planning time (d) is the time for planning to teach KORI at the beginning of whole activity. That would be shown the participant's such as self-efficacy and goal orientations.

Concept teaching time (d) Concept teaching time (d) is the duration of putting in the correct propositions and taking out the incorrect propositions among 15 propositions while teaching the basic concept on the various rocks to KORI.

Concept map teaching time (d) Concept map teaching time (d) is the duration of the drawing concept map. That contains concepts and relations among these concepts.

Response to interruption (t) Response to interruption (t) is the responding time to interruption stimulus such as KORI's sleeping faces and various emotive facial expression.

Correct concepts putting in (n) Correct concept selection (n) is the number of correct propositions put in. That reflected participant's knowledge level indirectly.

Correct concepts taking out (n) Correct concept selection (n) is the number of wrong propositions taken out. That also means participant's knowledge about 'rock cycle' indirectly.

Individual characteristics

The results indicated that each of the four measures of individual characteristics (self-efficacy, metacognition, learning goal, and performance goal) was correlated with the several learner responses.

Self-efficacy The pattern of the learner responses in teaching KORI turned out to be quite different depending on the level of self-efficacy. It was found that participants who were highly self-efficacious were likely (ⅰ) to spend more time in exploring learning resources; (ⅱ) to teach more correct concepts; (ⅲ) to show less difference between each learner's actual science test score and the predicted score of KORI at the end of the teaching, indicating that those who had high self-efficacy tend to estimate the score of KORI based on their actual test score.

Metacognition Metacognition is found to be the most significant individual characteristic to influence participants' responses during the interaction with the KORI. The result indicate that participants who had higher metacognitive awareness have a tendency (ⅰ) to spend less time in exploring the learning resources, indicating they know what they need to teach KORI and where the correct information; (ⅱ)to spend less time to predict the performance of KORI at the end of teaching; (ⅲ)to show estimation score low; (ⅳ)to show less difference between each learner's actual test score and the predicted score of KORI at the end of the teaching, indicating that those who had high metacognitive awareness are likely to estimate the score of KORI based on their actual test score.

Learning goal The student model showed that the level of learning goal orientation affected participants' response pattern. Participants who have high goal orientation were likely (ⅰ) to spend more time in exploring the learning resources; (ⅱ) to spend less time to predict the performance of KORI at the end of teaching; (ⅲ) to show more difference between each learner's actual science test score and the predicted score of KORI at the end of the teaching indicating predicting performance quickly but the correctness of KORI's learning level is incorrect. It might be explained high learning goal student relatively little focused on the quantitative outcome.

Performance goal Performance goal orientation was also related to some of the participants' responses. High performance goal oriented participants tend (ⅰ)to spend less time to predict the performance of KORI at the end of teaching, this variable negatively correlated with learning outcome interest that means these participant's relatively feel less interest during this teaching activity; (ⅱ)to show less difference between each learner's actual science test score and the predicted score of KORI at the end of the teaching. This result might support prior studies that performance goal don't have positive effect on motivation.

Learning outcomes

It was found that, among eleven primary learner response, the duration and frequency of exploring the learning resource, the planning time, the estimation duration of KORI's performance, difference between performance and estimation, and the response to interruption were correlated with the interest ratings whereas the duration of exploring the learning resource, the number of correct concept selection and wrong concept taking out, the duration of concept and concept map teaching and the difference between and the actual science test score of the learner and the predicted score of KORI were correlated with the comprehension test score.

Interest The results indicated that participants who were more interested in teaching KORI were likely (ⅰ) to spend more time in exploring the learning resources; (ⅱ) to spend more time to plan to teach KORI; (ⅲ)to explore learning resources more frequently; (ⅳ)the reaction time to interruptive stimulus; (ⅴ) to show more difference between each learner's actual science test score and the predicted score of KORI at the end of the teaching; (ⅵ)to spend less time to estimate the KORI's performance.

Comprehension The results showed that participants who understood more correctly after teaching KORI were likely (ⅰ) to spend more time in exploring the learning resources; (ⅱ) to teach more correct concepts; (ⅲ) to draw more correct concept map; (ⅳ)to show more difference between each learner's actual science test score and the predicted score of KORI at the end of the teaching.

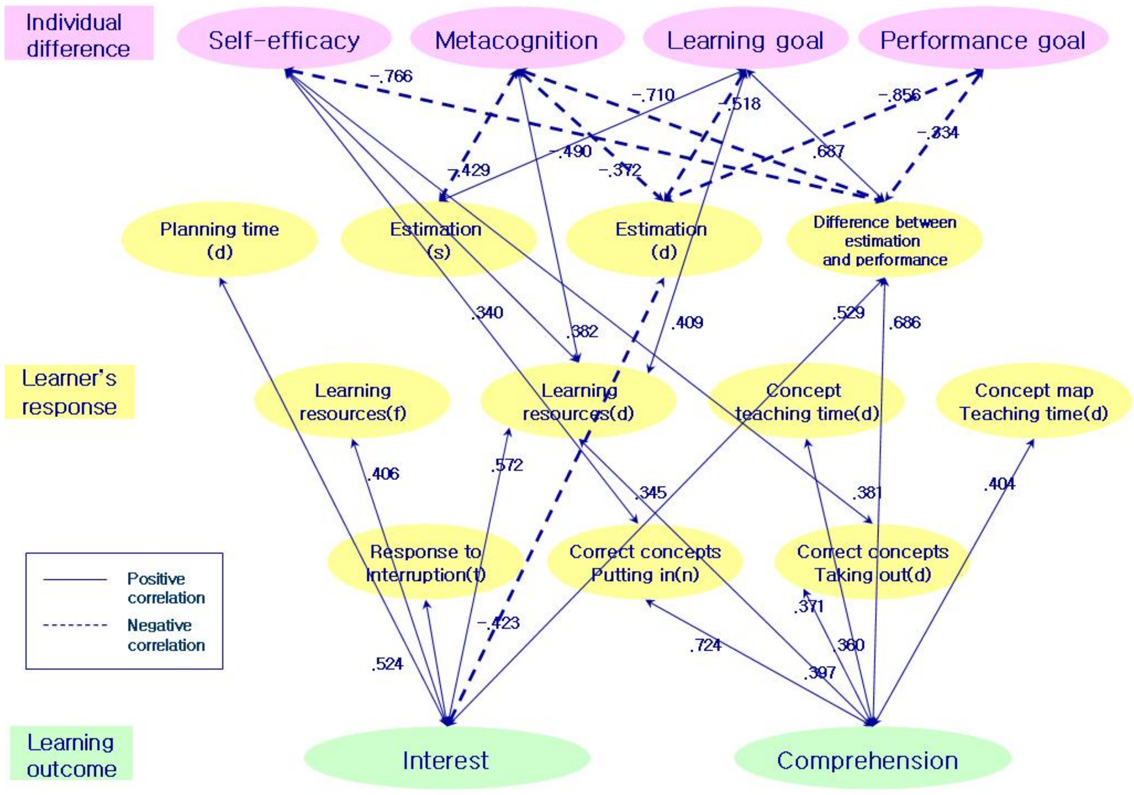

Figure 3: Structure of nodes (d: duration, f: frequency, n: number)

CONCLUSION

The results of student modeling indicate that participant's individual differences in metacognition, self-efficacy, goal-orientation and ongoing status of learning can be estimated by the combination of a variety of learner responses during the learning process. In the student model, all data were classified into three dimensions and described in terms of these three dimensions: individual differences, participants' responses, and learning outcomes. The participants' responses correlated with four individual characteristics or cognitive and motivational learning outcomes which are the planning time to teach KORI, the difference between performance and estimation, duration and frequency of exploring learning resource, the latency for performance estimation, the duration and frequency of concept and concept map teaching, and reaction time to interruptive stimulus. The difference between performance and estimation response is the only one that is combined. This response has relation with all 4 individual characteristics. In each individual characteristic, students with high level of the feature show the less different. And the learning resources exploration duration and difference between estimation and performance variables has relation both interest and comprehension. These participant responses are the useful indices to estimate the individual differences and the level of comprehension and interests of each learner.

Individualization is the key concept in developing computer assisted learning system and intelligent tutoring agent. The ultimate goal of developing the learning agent is to make an adaptive agent respond intelligently for individual learner, which reflects the individual differences in the level of cognition and motivation, and its ongoing changes. Traditional measurements in learning systems include assessing individual differences by standardized test or questionnaires at the beginning or at the end of the learning session. This study proposed a new type of dynamic assessment for individual differences and ongoing cognitive/motivational learning outcomes through the computation of responses without measuring them directly. In near future, various physiological indices such as temperature of fingers, eye-movement, facial expression, and brainwaves combined with the response pattern are likely to be used to measure individual differences or learning outcomes. However, for the time being, it is essential to develop the algorithm of learner response pattern during learning.

Collecting and classifying the indirect log data of the learner that are correlated with the individual differences and learning outcome, and constructing the student model consisted of the structure of nodes may be the useful methodology to understand the learner’s dynamic change during the specific learning situation.

The limitation of this study is that the log data were collected from very small sample. If the sample size is large enough, it would be possible to conduct a regression analysis to give the different weight on each response. Then the algorithm for adaptive teachable agent would be computed from the regression equation. If we extract the algorithm, agent collect the information of learner's learning states from the responses and can automatically predict the learner's cognitive and motivational states, then response differently based on the learner's specific situation.

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