

# A MODEL FOR PERSONALIZED INTELLIGENT TUTORING SYSTEMS

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## Abstract

Teaching and learning have been the most important issues from psychologists point of view. With the advent of computers to the world of science, researchers have tried to design intelligent tutoring systems to benefit from this technology as a useful tool for teaching and learning. Since each person has a learning style according to his/her personality and with considering the impact of affects in learning process, researchers have tried to use these parameters to personalize learning environment and make it adaptable to the user's needs.

This paper, for the purpose of improvement of learning process, models the learner with determining his learning style and estimating affects during learning. The proposed system teaches the student with his learning style, and then gives him a test to assess his learning. In order to interact with student while teaching and testing, a rule-based expert system which uses fuzzy concepts and certainty factors is made. System gets the degree of student's learning style and affect, fuzzifies them, and proposes educational tactics to the animated agent in user interface. The agent applies these tactics in system and interacts with student to make the environment appealing.

In order to evaluate the system, another version prepared in which modeling the user was omitted. Educational impact of main version was 24% more than the other version. Moreover, whereas main version received 7.32 of 9 in user interface satisfaction evaluation, the other version just received 6.8 of 9. Keywords: intelligent tutoring system, learning style, affect, rule-based expert system, agent

## 1. Introduction

Teaching and learning always have been one of the most basic human needs and simplifying and making them pervasive have been one of the researcher's concerns. In relation with formal learning and sometimes informal, a lot of intelligent tutoring systems have been made and used.

Intelligent tutoring systems have users who have different knowledge, learning styles, interests, background and preferences. This has paved way to research on interfaces that can be designed to recognize the goals and characteristics of the

user and adapt accordingly. In order to achieve adaptability of personalized information, it is important to observe the user's behavior, and make predictions based on those observations. The information pertaining to individual user obtained from such observation is known as a user model. A user model may consist of information collected by filling questionnaires, by observing user- actions, or by making inferences. Personalization aims at providing users with the content that they need without necessarily requiring the users to specify it explicitly [1].

Each student has his/her own learning style. Interfaces that can adapt according to that learning style are so desirable in intelligent tutoring environments.

Many researchers now feel strongly that intelligent tutoring systems would be significantly enhances if computers could adapt according to the emotions of students. This idea has spawned the developing field of Affective Tutoring Systems (ATSS). ATSSs are ITSs that are able to adapt to the affective state of students in the same ways that effective human tutors do [2].

This paper figures on designing intelligent user interface for tutoring systems. Using this system, students find it as it is designed just for them, feels their emotions and shows appropriate reaction.

In section 2 we present a concise overview of related work on making intelligent tutoring system and a brief primer on learning styles and emotions. In section 3 we explain our proposed model and discuss the implementation and evaluation of that model in section 4. Section 5 discusses the results and section 6 includes conclusions and future work.

## 2. Related Work

In this section, we discuss related work focused on intelligent tutoring systems and a brief explaining of learning styles and emotions.

Aplusix is an ITS for algebra, investigates whether high-performing students' experience of affect is different from that of low-performing students. The results show that students with the highest number of correct answers experienced flow the most while students with the lowest number of correct answers experienced confusion and boredom the most. Students who took the longest time in solving the al-

gebra problems experienced confusion the most. Students who used the most number of steps to solve a problem experienced confusion and boredom the most. This tutoring system uses a team of six observers to recognize affective states of the students and system logs all user interactions [3].

MITS is an affective tutoring system which detects the attention information and affective state and uses the information to drive the agent tutor to individualize interaction with the learner [4].

Easy with Eve is an affective tutoring system in the domain of primary school mathematics. The system adapts to students via a lifelike animated agent called Eve, who is able to detect student emotion through facial expression analysis, and can display emotion herself. Eve's tutoring adaptations are guided by a case-based method for adapting to student states. This method uses data that was generated by an observational study of human tutors [2].

Personality and individual differences are effective parameters in learning. In a research a model is designed based on the learner's personality. A questionnaire is used to determine the learning style according learner's personality. Then an expert knowledgebase select a suitable Virtual Classmate Agent (VCA) for learner. The VCA selects tactics to interact with the learner and will be able to cooperate intelligently with him/her. The results show that the presence of the VCA leads advancements in the learning process and attractiveness of virtual learning environment [5].

Human tutoring is a solution that students, parent and teachers use when students don't get ideal grades in school. Guru is a computerized tutor which models expert human tutors. Guru is an ITS in which an animated tutor agent engages the student in a collaborative conversation. This system is modeled after 50 hours of expert human tutor observations that revealed markedly different pedagogical strategies from previously observed novice tutors. This system which covers biology topics uses virtual pedagogical tools and some exercises for better learning [6].

## A. Learning styles

Comprehensive study of cognitive physiology shows that people have considerable individual differences in problem solving and decision making. Most of these differences are called learning styles [5].

Everyone has a different learning style and learns better via different methods. Learning styles are the variety of people capabilities in information gathering. In other word, learning style is the method that lets someone to collect knowledge and use it best.

Fleming and Mills (1992) suggested four modalities that seemed to reflect the experiences of the students and teachers. The acronym VARK stands for Visual, Aural, Read/write, and Kinesthetic sensory modalities that are used

for learning information. These modalities are discussed in brief:

**Visual:** This preference includes the depiction of information in maps, spider diagrams, charts, graphs and all the symbolic pointers and other devices, which people use to represent what could have been presented in words.

**Aural:** This perceptual mode describes a preference for information that is heard or spoken.

**Read/write:** This preference is for information displayed as words.

**Kinesthetic:** This modality refers to the perceptual preference related to the use of experience and practice (simulated or real) [7].

In this paper the VARK questionnaire is used to determine students learning styles. With asking 16 questions, the student's learning style which may be visual, aural, read/write or kinesthetic is determined. The point of each style would be between 1 and 16. Whatever the point is larger, the learning style would be more definite and so students would learn better with that style.

## B. Emotions

There are several different ways that computers can attempt to identify the affective state of users. These can be divided to two main groups: methods that aim to detect emotions based upon their physical effects, and methods that aim to predict emotions based upon understanding their causes [2].

Although being static, questionnaires are the tools for predicting emotions and can be useful means for detecting motivational traits and more enduring characteristics of the students [8].

Academic settings abound with achievement emotions such as enjoyment of learning, hope, pride, anger, anxiety, shame, hopelessness, or boredom. These emotions are critically important for students' motivation, learning, performance, identify development and health. AEQ or Achievement Emotion Questionnaire is a self report instrument measuring various emotions that students commonly experience in academic settings [9].

Among nine emotions studied in this questionnaire, boredom and hopelessness are discussed in this paper.

## 3. Proposed Model

We call the proposed model PATS which stands for Personalized Affective Tutoring System. In this model student's learning style and emotions are the factors for personalizing the learning environment. Both of them are linguistic variables and can be fuzzified. Students fill the questionnaires discussed above in the first time using the system, and the

facts about their learning style and emotions will be asserted to the knowledgebase. System starts teaching according to the student's learning style and then a test with 10 questions of different levels will be given to them. One of the other facts of the knowledgebase is the difficulty level of the questions which are answered wrong. This model is shown in Figure 1.

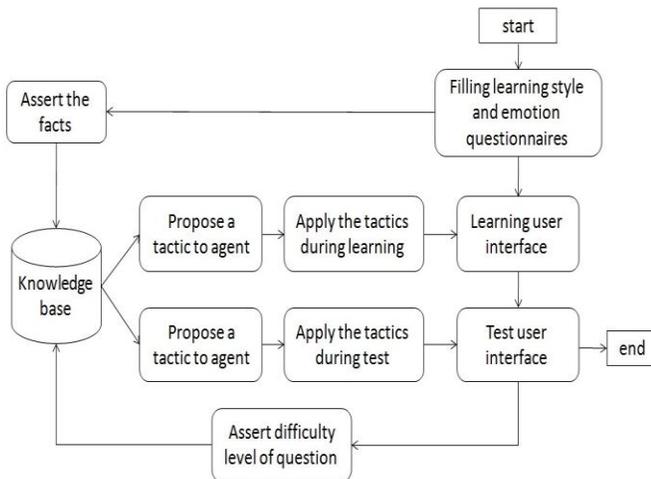


Figure 1. The proposed model named PATS for personalizing learning environment

As shown in Figure 1, system asserts the information as facts to the knowledgebase before learning and during test, and through its inference engine fires the rules which are matched with these asserted facts. The proposed tactics will be given to the agent in the user interface and agent applies them.

#### 4. Implementation and Evaluation

This paper for improvement of learning process through personalizing learning environment has developed a rule-based expert system on the basis of the model discussed in the prior section.

This expert system supports fuzzy concepts and certainty factors and is made with FuzzyClips shell. The other part of the system is the user interface in which teaching the educational content and interaction with agent is done and is programmed with Visual Studio.Net.

One of the important parts of the production of an expert system is knowledge acquisition. For producing the rules of the knowledge base of the system, we used a standard questionnaire with 54 closed questions. The questionnaire has two parts for learning and test, and asks from participants to choose an appropriate educational tactic by knowing the degree of students' learning style (poor, average or rich),

level of boredom and hopelessness (low, medium or high) and level of question difficulty(easy, normal or hard).

The questionnaires were given to 28 teachers (experts) and according to the number of experts who chose a tactic, a certainty factor was given to the rules of the expert system. Figure 2 shows a sample of these rules.

In this rule we can see for a situation that the degree of learning style is rich but student feels hopelessness high and has answered an easy question wrong, the expert system proposal would be not showing the answer to the student with certainty of 0.67.

```
(defrule 73
  declare (CF 0.67)
  (learning-style rich)
  (hopelessness high)
  (question easy)
  =>
  (assert (agent tactic not-show-answer))
)
```

Figure 2. A rule in the PATS knowledgebase produced from the answers of 28 experts to the questionnaires explained above

Then agent will apply the tactic with the highest certainty in the user interface. The pseudo code of the process taking place in PATS fuzzy expert system is shown in Figure 3.

```
Pseudo code of PATS fuzzy expert system
Input: crisp values of learning style, boredom, hopelessness and question
Output: pedagogical tactic proposed to agent

for each student do
  Begin
    get the crisp value of her/his learning style;
    get the crisp value of her/his boredom and hopelessness level;
    assert above information as facts to the knowledgebase;
    firing the rules that match asserted facts;
    proposing results as learning tactics to agent;
    for each question answered by student do
      if answer is wrong
        begin
          assert question number as a fact to knowledgebase;
          firing the rules that match asserted facts;
          proposing results as test tactics to agent;
        end
      end
  end
```

Figure 3. The pseudo code of PATS fuzzy expert system

In Figure 3 we can see the inputs and outputs of the system. The system gets the crisp values of learning style and boredom from the questionnaires filled by students and also

the degree of the questions' difficulty as the inputs. Then during learning and test fires the rules which are matched with those facts and proposes a tactic.

Also to make the learning environment attractive and apply the expert systems' proposed tactics in the user interface of PATS we selected Merlin agent Microsoft agents.

In order to evaluate the educational impact of PATS and study the effects of personalization factors in the success of the system, two versions of PATS were produced.

First version: the learning environment without user model

Second version: the learning environment with user model

In the first version students' learning style is determined with the VARK questionnaire but system teaches the student according to style which obtained lowest point. In this version there is no emotion, no expert system and no agent to interact with learner. But the second version is the main which was explained earlier in the implementation section.

To compare the performance of two versions, system was given to 24 students. 12 learned with first version and 12 with second version. All the participants were female. Almost half of the participants in each team were high-performing students.

Also to evaluate the user interface of PATS, we used QUIS-Questionnaire for User Interface Satisfaction- that is developed in Maryland University. This questionnaire has 27 questions and is organized in five sections including overall reaction to the software, screen factors, terminology and system feedback, learning factors and system capabilities [10]. The questionnaire was given to all participants using two versions.

## 5. Results and Discussion

Figure 4 shows the comparison of students' learning using two version of the system. Average of correct answers in the test was used for this reason.

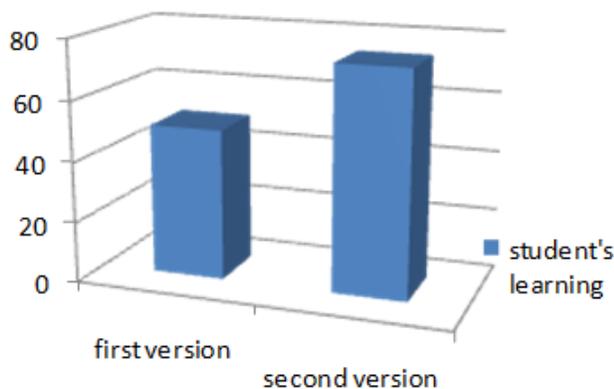


Figure 4. Evaluation of student's learning in two versions of PATS environment

As it is shown in Figure 4 students' learning in the first version environment which doesn't have personalization factors is 50%, while it has reached 74.1% in the second version.

Figure 5 illustrates the results of QUIS that is also a comparison between two versions of the system. Darker bars show the satisfaction of first version and lighter bars shows that of second version. As it is shown in all 5 sections of evaluation second version has obtained more satisfaction. Also the results show that in total average satisfaction of second version is 7.23 out of 9, while it is 6.8 out of 9 for the first version.

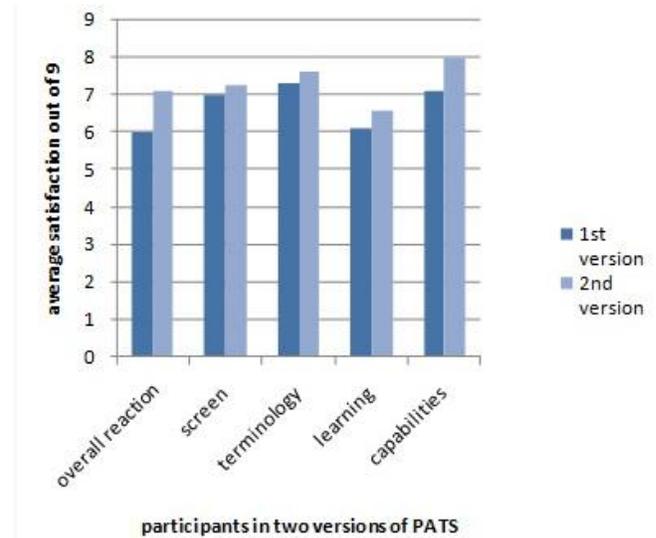


Figure 5. Results of evaluating QUIS for two versions of PATS

## 6. Conclusion and Future Work

Personalization of learning environments has significant impact in learning process improvement. This paper has presented a model that combine learning styles and emotion as two factors to improve this process. In the proposed model only two negative emotions – boredom and hopelessness- are used. We can improve our model with considering other emotions like shame, anger and stress and proposing solutions to omit these emotions during learning process. This model chooses the learning style which has the highest point in the questionnaire, but in the future we can consider multimodal learning styles that are a combination of two or more styles.

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## References

- [1] J. Baskar, H. Lindgren, D. Surie, C. Yan, and F. Yekkeh, "Personalisation and User Models for Support in Daily Living," The 27th annual workshop of the Swedish Artificial Intelligence Society (SAIS), 2012, p. 7.
- [2] S. Alexander, A. Sarrafzadeh, and S. Hill, "Easy with eve: A functional affective tutoring system," Workshop on Motivational and Affective Issues in ITS, 2006, pp. 5–12.
- [3] M. C. V. Lagud and M. M. T. Rodrigo, "The affective and learning profiles of students using an intelligent tutoring system for algebra," Intelligent Tutoring Systems, 2010, pp. 255–263.
- [4] X. Mao and Z. Li, "Agent based affective tutoring systems: A pilot study," Computers & Education, vol. 55, no. 1, pp. 202–208, 2010.
- [5] S. Fatahi, N. Ghasem-Aghae, and M. Kazemifard, "Design an expert system for Virtual Classmate Agent (VCA)," Proceedings of the World Congress on Engineering, London, UK, 2008, vol. 1.
- [6] A. M. Olney, S. D'Mello, N. Person, W. Cade, P. Hays, C. Williams, B. Lehman, and A. Graesser, "Guru: A computer tutor that models expert human tutors," in Intelligent Tutoring Systems, 2012, pp. 256–261.
- [7] N. D. Fleming, "The VARK Categories," <http://www.vark-learn.com/english/page.asp?p=categories>, 2012.
- [8] A. de Vicente and H. Pain, "Motivation diagnosis in intelligent tutoring systems," 1998, pp. 86–95.
- [9] R. Pekrun, T. Goetz, A. C. Frenzel, P. Barchfeld, and R. P. Perry, "Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ)," Contemporary Educational Psychology, vol. 36, no. 1, pp. 36–48, 2011.
- [10] K. L. Norman, B. Shneiderman, B. D. Harper, and L. A. Slaughter, "Questionnaire for user interaction satisfaction," University of Maryland, Human-Computer Interaction Laboratory, College Park, MD, 1998.

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