

# AN EMOTIONAL EXPRESSION MODEL FOR EDUCATIONAL-SUPPORT ROBOTS

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## Abstract

With the growth of robot technology, robots that assist learning have attracted increasing attention. However, users tend to lose interest in educational-support robots. To solve this problem, we propose a model of emotional expression based on human-agent interaction studies. This model in which the agent autonomously expresses the user's emotions establishes effective interactions between agents and humans. This paper examines the psychological effect of a robot that is operated by the model of emotional expressions and the role of this effect in prompting collaborative learning.

## 1 Introduction

The growth of robot technology has prompted an increasing interest in robots that assist learning. For example, an educational-support robot can assist students throughout their school life [1] or help English learners acquire or improve their English language skills [2]. Educational-support robots have been investigated in numerous studies. For example, Koizumi [3] developed a robot-run series of Lego-block building classes. The robots achieved collaborative learning among children and established positive social relationships with them by praising their efforts. These experimental results suggest that, besides stimulating spontaneous collaboration, robots enhance children's enthusiasm for learning.

Despite these successes, students gradually lose interest in teaching robots as learning progresses. A previous study [4] showed that college students were initially interested in the robot but began to neglect it as their learning evolved.

Diminishing interest in robot-assisted learning has been tackled by various methods. This study focuses on an emotional expressions model in which the agent expresses autonomous emotions. This model has proved beneficial for agent-human interactions, because robots expressing focused emotions more effectively interact with humans than robots expressing random emotions [5]. Moreover, collaborated human learning is promoted when the agent presents a positive expression rather than a negative expression or no emotion [6]. However, the emotional expressions model has not been adopted in an educational-support robot. Therefore, the mechanism of this model in an educational-support robot remains unknown.

To fill this gap, the present study proposes a model of emotional expressions for educational-support robots. Moreover, we examine the psychological effects of an emotion-expressing robot on the ability of learners to collaborate. This study relies on Russell's circumplex model of affect [7] in which the emotional state is described in a two di-

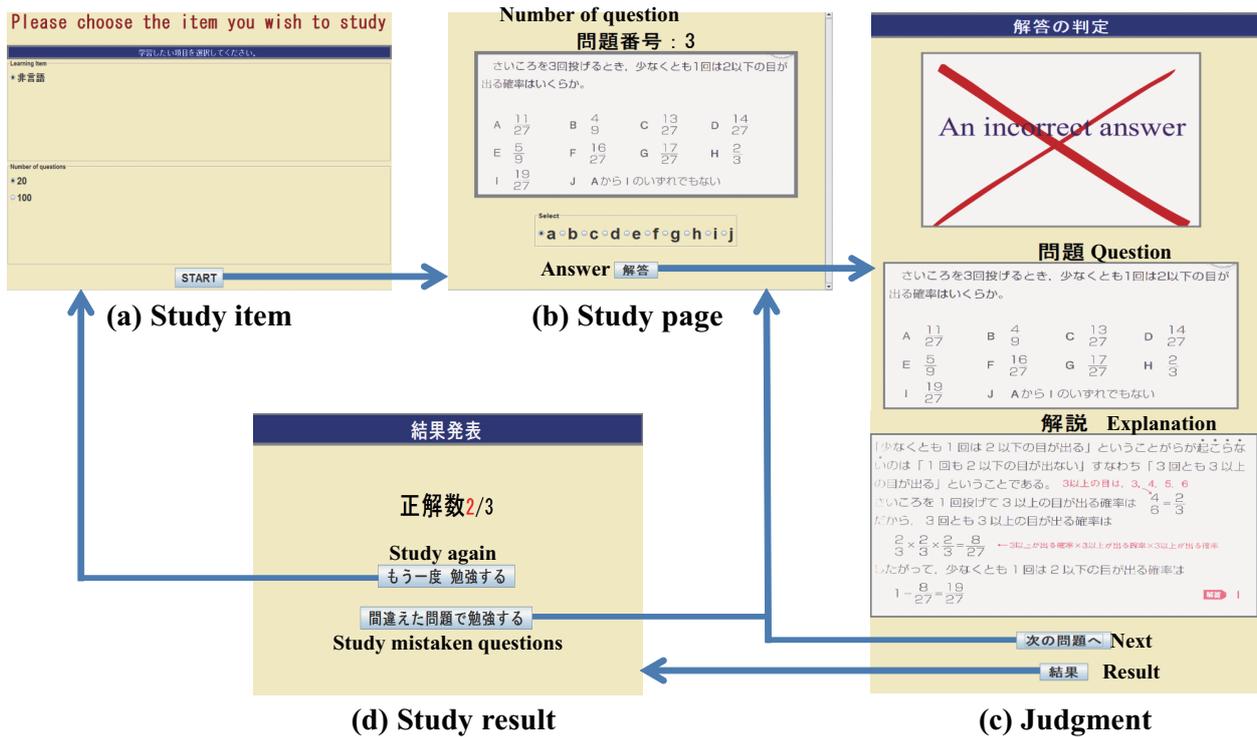


Figure 1. Learning System

dimensional coordinate system of arousing-sleep and pleasure-displeasure. The points on this plot determine the emotions expressed by the agent. In an existing study of a learning system using a screen agent, learning motivation was enhanced when the agent expressed sympathy toward the learner [8]. Our proposed circumplex model express the agent's emotion as two points in the above-described coordinate system. The correct point corresponds to a correct answer of the learners, whereas an incorrect point represents an incorrect answer. The robot using the proposed model is assumed to sympathize with learners and allow them to enjoy collaborative learning.

## 2 Overview of the learning system

The learning system is the “synthetic personality inventory 2 (SPI2)” (Figure 1), which is typically used for recruitment. It comprises junior-high-school level mathematical problems such as profit and loss calculations as well as fee payments. Therefore, college students require no additional

knowledge. The problems were created by consulting the “2014 SyuSyokukatudou no Kamisama no SPI2 mondaisyu (in Japanese) [9].”

Learners log into the system by entering their account number, and a menu of study items appears (Figure 1a). The learner selects the number of problems to solve from the column under the study items. For example, if the learner selects “20,” twenty problems are displayed at random. If “20” is selected again, twenty different problems are displayed. This process can be reiterated until all problems have been solved (20 problems  $\times$  5 sets), allowing learners to solve their problems within the selected study item. Once the learner selects the study item and the number of problems, the learning screen (Figure 1b) appears, starting the learning process. The learner chooses an answer to the problem from the provided list and the system indicates whether the answer is correct or incorrect (Figure 1c). When the learner selects “next” (Figure 1c), the system moves to the next problem. When the learner selects “result” (Figure 1c) or solves all problems, the system displays the number of correct and incorrect answer on the results page (Figure 1d). The “study again” option re-displays the menu of learning items and the learning process re-

peats (Figure 1a). Finally, when the learner selects “study mistakes,” the study page presents the incorrectly answered problems (Figure 1b).



Figure 2. Appearance of Ifbot

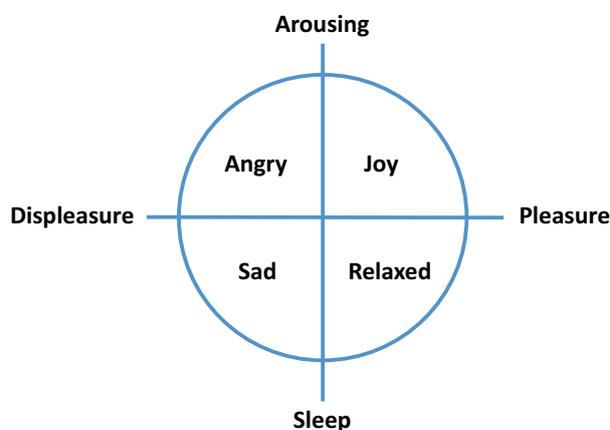


Figure 3. Russell's circumplex model of affect

### 3 Overview of the robot

#### 3.1 Robot

This study utilizes the communication robot Ifbot (Figure 2), which is commonly adopted for English language learning and effective learning [4]. This robot can also display various expressions. The learning system is implemented in Ifbot, enabling Ifbot and students to face the monitor and learn together.

#### 3.2 Russell's circumplex model of affect

The emotions of the robot rely on the Russell's circumplex model of affect [7](Figure 3), which has previously facilitated human-robot interactions. Moreover, this earlier report suggests that the agent, which uses Russell's circumplex model of affect, can prompt more effective interactions with humans than an agent using a conventional model [5]. In addition to the proposed model, this previously described conventional model, which utilizes one coordinate point to express emotions, is also evaluated for comparison.

The robot's emotions are based on Russell's circumplex model of affect [7](Figure 3), which has previously facilitated human-robot interactions. According to an earlier report, an agent programmed with this model more effectively interacts with humans than an agent using a conventional model [5]. Here, we adopt the conventional model, in which emotions are represented by a single point for comparison with the proposed model. The circumplex and conventional models are illustrated in Figs. 4 and 5, respectively. In each model, the pleasure-displeasure and arousing-sleepy axes correspond to the number of correct answers and the answer time(time required for the learner to answer the question), respectively. Each axis ranges from  $-1.0$  to  $1.0$ . Emotions expressed by the robot are determined by the angle between the point and the pleasure-displeasure.

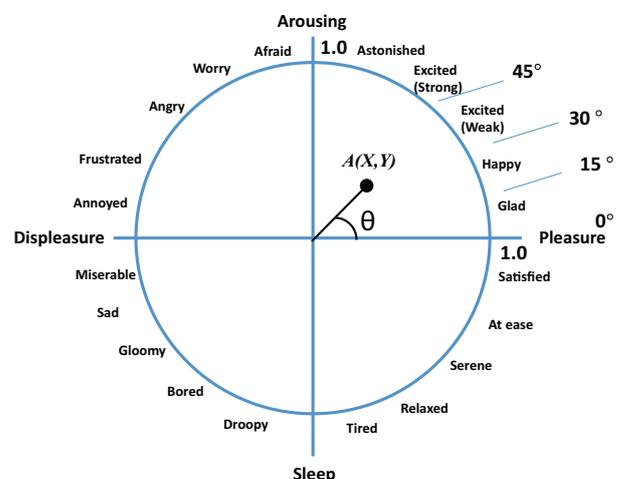


Figure 4. Conventional model

### 3.2.1 Conventional model

In the conventional circumplex model, emotions are represented by the coordinate point  $A(X, Y)$ , where  $X$  and  $Y$  refer to the alertness-sleepiness and arousing-sleepy axes, respectively. The coordinate point  $A(X, Y)$  varies by the following rules.

*if*(answer is correct.)

$X \leftarrow X + 0.2$

*else*

$X \leftarrow X - 0.2$

*if*(Answer time < Basic time)

$Y \leftarrow Y + 0.2$

*else*

$Y \leftarrow Y - 0.2$

The basic time defines the average answer time determined in a preliminary experiment on eighteen subjects practicing the learning system. The answer time was measured during this learning period and averaged as 85.5 s. Therefore, the basic time was set to 85.5 s. Twenty-four emotions arranged at  $15^\circ$  intervals (Figure 4) were evaluated. Emotions expressed by the robot were determined from the angle  $\theta$  of coordinate point A. For example, if  $\theta$  lies within  $0^\circ$  and  $15^\circ$  ( $0 < \theta \leq 15$ ), the robot expresses “glad.” If  $\theta$  ranges within  $15^\circ$  and  $30^\circ$  ( $15 < \theta \leq 30$ ), the robot expresses “happy.”

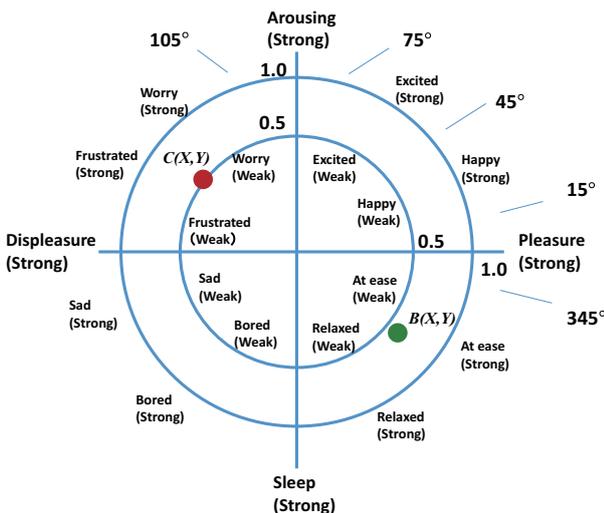


Figure 5. Proposed model

### 3.2.2 Proposed model

Because students are more motivated to learn when the agent is sympathetic [8], the pro-

posed model expresses emotions by two coordinate points. In this model, coordinates  $B(X_B, Y_B)$  and  $C(X_C, Y_C)$  correspond to correct and incorrect answers, respectively.  $X_B$  is between 0 and 1.0, and  $Y_B$  is between  $-1.0$  and  $1.0$ . On the other hand,  $X_C$  is between  $-1.0$  and  $0.0$ , and  $Y_C$  is between  $-1.0$  and  $1.0$ . Here, the  $X$  and  $Y$  axes correspond to alertness-sleepiness and arousing-sleepy respectively, as before. The coordinate points  $B(X_B, Y_B)$  and  $C(X_C, Y_C)$  vary by the following rules.

*if*(answer is correct.)

$X_B \leftarrow X_B + 0.2$

$X_C \leftarrow X_C + 0.1$

*else*

$X_B \leftarrow X_B - 0.1$

$X_C \leftarrow X_C - 0.2$

*if*(Answer time < Basic time)

*if*(answer is correct.)

$Y_B \leftarrow Y_B + 0.2$

*else*

$Y_C \leftarrow Y_C + 0.2$

*else*

*if*(Answer is correct.)

$Y_B \leftarrow Y_B - 0.2$

*else*

$Y_C \leftarrow Y_C - 0.2$

As in the conventional model, the basic time is set to 85.5 s. Twenty-four emotions (12 strong and 12 weak) are arranged in  $30^\circ$  intervals, as shown in Figure 5. Emotions expressed by the robot are represented similarly to the conventional model. For example, “glad” in the conventional model corresponds to “happy” (weak) in the proposed model. These emotions are represented by the angle  $\theta$  of coordinate points B or C; if  $\theta$  lies within  $15^\circ - 45^\circ$  or  $45^\circ - 75^\circ$ , the robot expresses “happy” or “excited,” respectively. Moreover, in this model, the strength of the emotion depends on the distance between the coordinate point and the center. If the coordinate point lies within 0.5 units from the center, the emotion is weakly expressed. Outside this 0.5 radius, the emotion is strongly expressed.

### 3.3 Robot action

This subsection examines the psychological effects of a robot programmed by the model of emotional expressions. Because the aim is to facilitate collaborative learning, features necessary for direct human interactions (such as voice recognition) are

not considered. Instead, the robot reacts to the screen of the learning system. Specifically, it is designed to make a happy or unhappy utterance when a learner solves a given problem (Figure 1d). Each happy and unhappy utterance comprises 12 patterns and corresponds to a particular emotion in the conventional and proposed models. The robot utters “Yes, the answer was right” when “happy” but “Oh no! Better luck next time” when “unhappy.” These actions give the impression of learning along with the student.

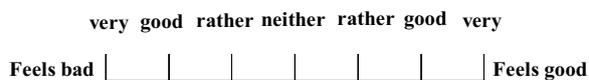


Figure 6. SD method used in this experiment

## 4 Examination

### 4.1 Method

The psychological effects of the robot were assessed on eighteen science college students divided into three groups. The proposed model group and the conventional model group learned with an Ifbot programmed by the proposed and conventional models, respectively. The robot in the control group expressed the same emotions as the conventional and proposed model robots, but expressed them randomly. When learners in the control group gave a correct answer, the robot randomly expressed an emotion on the positive side of the x-axis ( $X > 0$ ). When learners gave an incorrect answer, they received a random emotion on the negative side of the x-axis ( $X < 0$ ).

Assisted by the robot, the learners solved 20 problems installed in the learning system. Moreover, to avoid the order effect, the students were divided into six subgroups, each comprising three students who completed collaborative human-robot learning in different orders.

### 4.2 Evaluation

Psychological effects were evaluated by the semantic differential scale (SD) method [10]. The learning experience was rated by ten terms: “feels good,” “warm,” “tender,” “emotional,” “round,”

“entertaining,” “kind,” “cheerful,” “humorous,” and “simple” (Figure 6). Evaluations ranged from  $-3$  (top left) to  $+3$  (top right).

The results were analyzed by one-way analysis of variance (ANOVA). Sub-effects were evaluated by Fisher’s protected least-significant difference (PLSD) [11]. Differences were considered significant at the 5% significance level ( $p < 0.05$ ).

### 4.3 Results

Average evaluation values for the proposed model group (left), the conventional model group (center), and the control group (right) are shown in Figure 7. The scores obtained by the proposed model group for feels good, humorous, simple, round, emotional, and entertaining were the highest. An ANOVA was conducted for each average value. These results are listed in Table 1. The first factor (A) corresponded to each group while the second factor (B) represented each score of the SD method. Table 1 revealed a significant difference between the groups. Therefore, Fisher’s PLSD was performed for each group (Table 2). These results showed a significant difference between the proposed model and control groups, which indicates that the learners from the proposed model group feel a more positive experience than the learners from the control group.

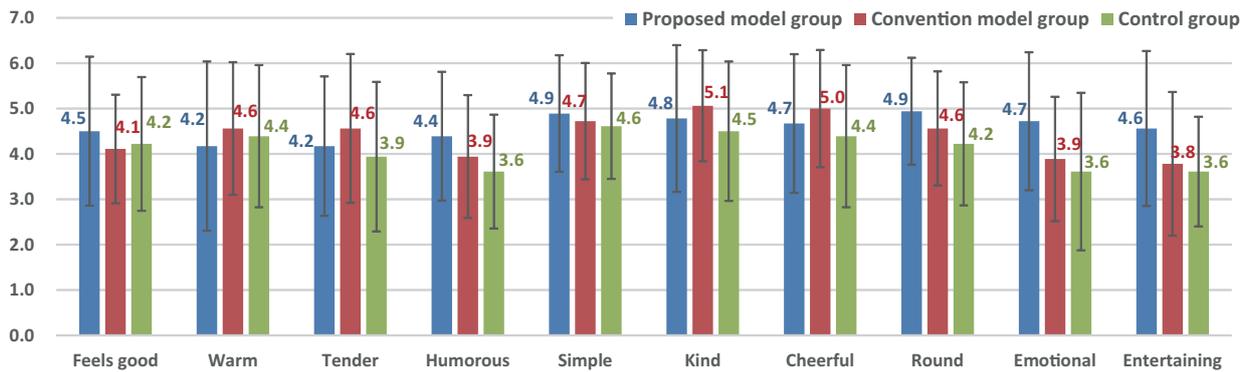
Table 1. ANOVA Results

	<i>F</i>	<i>df</i>	<i>p value</i>
A(Each group)	4.48	2,539	0.023
B(Each score)	2.30	2,539	0.094
Interaction of A*B	0.60	2,539	0.555

Table 2. Fisher’s protected least-significant difference scores of sub-effects

	<i>T</i>	<i>p value</i>
Proposed * Conventional	1.02	0.31
Proposed * Control	2.94	0.00
Conventional * Control	1.93	0.06

The average evaluation scores of the proposed model group (left), the conventional model group (center), and the control group (right) are shown in Figure 7. Among the three groups, the proposed model group gave the highest ratings for “feels good,” “humorous,” “simple,” “round,”



**Figure 7.** Semantic differential scores of the human-robot learning experience

“emotional,” and “entertaining.” ANOVA analyses of the average scores are listed in Table 1. The first and second factors (A and B, respectively) denote the group and individual scores of the SD method, respectively. As significant differences were found among the groups (Table 1), each group was evaluated by Fisher’s PLSD (see Table 2). The Fisher’s PLSD revealed significant differences between the proposed model and control groups, indicating that the learning experience was more positive in the proposed model group than in the control group.

## 5 Discussion

According to the results, the proposed model provides a more positive learning experience than random expressions during collaborative human-robot learning. These findings may be explained by two factors-sympathy of the robot toward human learners and the expression of autonomous emotions. Previous studies have indicated that a sympathetic agent enhances learning motivation [8] and that agents expressing appropriate emotions can better interact with humans than those expressing random emotions [5]. Here, we observed a similar effect during collaborative human-robot learning.

## 6 Conclusions

This study proposes a model of emotional expressions for educational-support robots. The psychological effects of a robot programmed with this model were examined during human-robot collaborative learning. Emotional expression was based on Russell’s circumplex model of affect, which repre-

sents an emotion by two coordinates. In the proposed system, one coordinate corresponds to a correct answer to the question and the other to an incorrect answer. The results suggest that, during collaborative learning, a robot expressing emotions by the proposed model generates more favorable impressions than a robot expressing random emotions. The psychological and learning effects during collaboration with a robot expressing autonomous emotions will be investigated in a longer term study.

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