



Building an Affective Model for Social Robots with Customizable Personality

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Abstract. As robot technology advances, there is a progressively growing demand to empower robots with human-like emotions. Designing appropriate personality features for social robots can enhance user contact with them as well as help them complete their works more effectively. In this paper, an affective model for social robots with adjustable personality is proposed. This model describes the changing process between emotional states using emotion, mood, and personality. Our model can convincingly mimic the emotional fluctuations of individuals with various personalities by using the results of experiments on real humans. First, we proposed a bowl-shaped affective model with eight fundamental feelings in three dimensions of emotional space, and then we provide a way for modeling personality. Second, we use the emotional arousal methods to contrast and examine how various personality groups responded to the same emotional stimulus. Based on this, we build two models that can fully capture introverted and extroverted personality traits, and then we use the validation data set to assess the validity and reliability of the parameters in our model. The results show that the model can effectively simulate the emotional change process of different personality groups after being subjected to varied emotional stimuli.

Keywords: Social robots · Affective model · Personality · Human-robot interaction

1 Introduction and Related Works

People now have higher expectations for robots as a result of the development of robot technology, which expands application scenarios for robots and makes it possible for robots entering people's daily lives from factories in recent years. For instance, people are more likely to consider robots as partners for projecting emotions than just to regard them as machines for completing tasks [1, 24], and robots that can replicate empathy sensitively will be much more well-liked by their users [2]. Building "natural" human-robot interaction (HRI) solutions with implicit communication channels and a certain level of emotional intelligence are therefore becoming increasingly crucial [3]. An affective model can make social robots better meeting user's needs. Additionally, affective models can be sensitive to empathy and satisfy the special demands of users. Therefore,

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an affective model which can be customized and shows some kind of “personality” can address the aforementioned problems.

Robot personality has not yet been adequately defined by academics. However, a person’s personality is characterized by their distinctive thought, emotion, and behavior patterns as well as the psychological mechanisms behind it [4, 25]. In terms of the user’s emotional demands, users have psychological expectations for the robot’s personality traits [5]. The robot’s personality has a substantial impact on the user’s behavior, experience, and appraisal in HRI [6–8], and in the long-term interaction process, the robot’s personality plays a role [9]. In terms of product functional needs, robots in different jobs need to have diverse personalities to fit their jobs. For example, companion robots must be kind and compassionate, and security robots may be expected to possess courage, among other traits [1, 10].

The development of accurate computational emotion models for robots has drew significant attention from researchers. There are two categories of robot emotion model programs: one is devoted to a more reasonable expression of emotions “externally”, while the other is devoted to an endogenous human-like emotion regulation “internally” of the robot [11]. We focus more on the latter. A small number of researchers have concentrated on the function of personality in emotion regulation in robots. In particular, Naoki Masuyama et al. [12] proposed an emotion model containing personality traits, memories, and five fundamental emotions with the P-A-D emotion space theory and the Big Five personality theory. They demonstrated how the emotions of robots with three different personality parameters changed. By modifying the personality suppression of expression parameters, Xue Hu et al. [13] built an emotion model for robots with various personalities and measured the emotion regulation process of Gross using the Hidden Markov Model (HMM). Meng-Ju Han et al. [14] developed an “emotion-mood-personality” three-level emotion model and showed three robots with various personalities by altering the parameters of the five-factor personality model. Itoh C et al. [15] proposed an emotion-generating model with emotion transmission to evaluate a robot’s personality and internal condition. However, the majority of studies have treated personality parameters as set variables rather than parameters to be adjusted, and this will result in our inability to test whether the robot’s personality achieves the desired effect, furthermore, we are also unable to accurately generate robotic personalities that meet the needs of users through models.

Our study proposes and validates a reliable robot personality creation approach, extending the work of Qi X et al. [16], and proposes a modeling method for a three-dimensional emotion space based on Plutchik’s wheel of emotions (PWE), with “emotion-mood-personality” as the emotional interaction mechanism.

This paper has the following contributions:

- (1) Propose a new approach to model a 3D emotional space, including theoretical and calculational mechanisms;
- (2) Suggest a method for creating various personality robots based on the affective model, simulates the various personalities that robots may need in a variety of scenarios, and confirms the validity of the personality model.

2 The Framework of Customizable Personality Affective Model (CPAM)

2.1 Overview of Previous Work PWE Inspired Affective Model

In our previous work [16], we have proposed a PWE [17] inspired affective model which can simulate the motivation of stimuli on emotions, emotion natural decay, and the effect of mood on emotional responses and emotional decay. The model contains 8 basic bipolar emotions together with the interactions with moods, and uses exponential decay processes to describe the natural changes of emotions and moods. The process of the affective changes is corresponding to different update equations in four conditions, which are based on comparing the combined effect and the single factor effect of the previous emotion, previous mood, and current stimulus. Any detailed discussion can be found in [16].

Personality is an important factor in understanding robot emotions during human-robot interaction [5, 17, 18]. Specifically, we believe that it is necessary to represent personality figuratively in the robot emotion model. The above model only lies in the differences between a few threshold parameters and the variable of personality bias, thus will make the differences in emotional change under different personalities incomplete and intuitive, and will influence us to shape the affect of a robot from the perspective of personality. And even further, there is still a lack of a clear parameterized method to explain the mechanisms involved in controlling the differences in affective change. To address the above problems of PWE, we propose an improved model named Customizable Personality Affective Model (CPAM).

2.2 Parametric Approaches to Personality

On the basis of the previous work, the interaction mechanism among emotion, mood, stimulus and personality is improved, shown in Fig. 1. It includes three instantaneous effects on emotion, and two cumulative effects produced by emotion and mood.

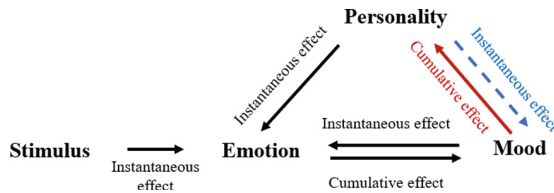


Fig. 1. The interaction mechanism among variables. (The blue dotted line belongs to our previous model, the red solid line belongs to the improved model, others belong to both two models) (Color figure online)

The improvement mainly focuses on the parametric definition of the two cumulative effects. In terms of mood update, as it lasts more longer and does not relate to specific events, we regard it as a cumulative effect of emotion, and model it as a state variable

that changes slowly.

$$m(t) = m(t - 1) + \Delta m \tag{1}$$

where t is the time that the event happened and i represents the corresponding emotion and Δm is the amount of change in every update period of mood dt .

And to map stimulus emotions into mood states, we simply adopt the mean emotion mapping function [19], as well as consider the two sources of effect including stimulus and natural attenuation of emotion.

$$\Delta m = \begin{cases} \frac{1}{n} \sum_{i=1}^w \alpha_i k_{ei} a_{it}, t \in [t_{i0}, t_{i0} + d_{it}] \\ \sum_{i=1}^8 \frac{\alpha_i \int_{t_s}^{t_s+dt} (e_i(t) - e_i(t_s)) dt}{dt}, \text{ otherwise} \end{cases} \tag{2}$$

where n is the number of dt while the stimulus still works, w is the total number of active emotions, α_i is the emotional polarity variable that divides emotions into positive ($\alpha_i = 1$) and negative ($\alpha_i = -1$) according to whether they are user-friendly or not, a_{it} is the intensity of the stimulus event, t_{i0} is the natural decay start time, k_{ei} is the influence factors of emotions to mood, d_{it} is the duration of stimulus that effects on emotion i , $e_i(t)$ is the intensity of emotion i at moment t , and t_s is the start time of each dt while the mood is naturally decaying.

Moreover, the previous research has documented that maintaining a unipolar emotional experience for a long time will affect personality shaping [20]. Accordingly a variable $m_{ac}(t)$ is defined to record the cumulative effect of mood that not in neutral state as in Eq. (3).

$$m_{ac}(t) = \begin{cases} \left| \int_{t_{ac}}^{t'_{ac}} m(t) dt \right|, \text{ if } R_3 \\ 0, \text{ otherwise} \end{cases} \tag{3}$$

$$R_3 : \forall m(t), t \in [t_{ac}, t'_{ac}], m(t) \in [-1, h_n] \cup [h_p, 1], m(t - 1) \in (h_n, h_p) \tag{4}$$

where t_{ac}, t'_{ac} are the beginning and the end of the period that satisfy R_3 , h_n and h_p represent 2 different thresholds that divide mood state into 3 intervals (positive, neutral, and negative mood states). When the absolute value of $m_{ac}(t)$ reaches a certain standard m_{ac} , it will cause changes in personality.

Following this we can give a clear definition of personality as the union of eight countable locus sets, in order to make the changes in personality caused by the mood has obvious concrete performance:

$$P = \bigcup_{i=8} P_i, \forall P_i \in \{P\}, P_i = \{p_{i0}, p_{i1}, \dots, p_{in_i}\}, n_i \in N \tag{5}$$

For any personality $P_x \in \{P\}$, each of its 8 subsets P_{ix} covers some loci of control $\{p_{ik}\}$ that consist of various degrees of stimuli and the corresponding emotional intensity it aroused.

$$p_{ik} = (e_{ik}(t_{i0}), a_{ik}), a_{ik} \in \{a_{it}\}, k \in n_i \tag{6}$$

These loci of control can concretely reflect the differences between various personalities. On the one hand, the loci of control shape a 3D model shown in next subsection, through which we can more intuitively observe differences in emotional traits exhibited by different personalities. On the other hand, they directly affect the computational parameters, which in turn play a decisive role in the model. Consequently, the changes in personality can be parameterized as changes in these loci of control.

In order to show the personality changes in a more intuitive parameterized way, we simply select 33 loci as observation objects, whose emotional intensity is equal to the emotional threshold. These loci are the most representative ones, thus we can observe the most obvious personality traits and changes by focusing on them. And the update equations for them can be written as follows.

$$h = \begin{cases} \frac{(m(t)-h')}{\beta*\beta'}, & \text{if } |m_{ac}(t)| > m_{ac} \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

$$\beta' = \begin{cases} 1, & \text{if } h_{ij} = h_{im} \\ \frac{h_{im}}{h_{ij}}, & \text{otherwise} \end{cases}, \quad h' = \begin{cases} h_n, & m(t) \leq h_n \\ h_p, & m(t) \geq h_p \end{cases} \quad (8)$$

where β and β' are the update factors of personality, and $\{h_{ij}\}$ contains all the emotional thresholds. For any selected locus of control (h_{ij}, a_{ik}), after an update process of personality, the new value will become ($h_{ij} + \Delta h, a_{ik}$).

In like manner, any remaining locus of control p_{ik} will also changes the emotional intensity aroused by the same stimulation. The change will follow a linear fit between two adjacent threshold loci of control.

2.3 3D Model Structure

On the basis of the affective model with detailed definition of personality, a 3D model that contains the emotion curves and balls can be proposed as shown in Fig. 2a. It can describe the spatial form of personality locus of control, and show the process of emotion change.

Compared with the previous 2D model [16], the 3D one can not only cover all the visualizations that the original model can display, but also having a huge advantage on showing the personality traits obviously, as well as visualizing the relationship between stimuli and emotions clearly.

Taking Fig. 2b as an example, for the same kind of personality we give a stimulus having the same intensity on both joy and trust. But even though the Joy-Ball and the Trust-Ball having the same spatial height, the horizontal projection distance of the Joy-Ball to its initial position is much longer than another. It's on this basis that we can conclude this personality having a more explicit characteristic on joy than on trust. Besides, focus on the two bowl-shaped affective model mentioned above, we can also analyze the traits of different personalities by comparing the spatial position of corresponding threshold loci, for instance, the personality in Fig. 2a can achieve more intense trust.

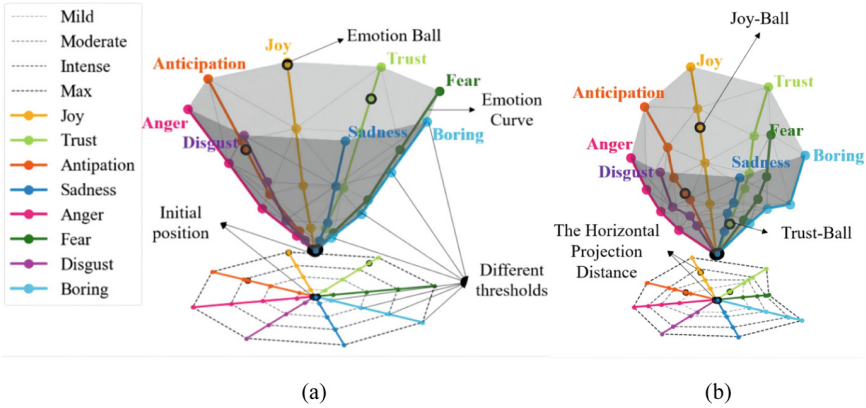


Fig. 2. The proposed 3D affective model. (a) The components of the model; (b) An example of the model.

3 Building Introverted/Extroverted Robot Affective Models

3.1 Questionnaire of Personality Parameters

To evaluate the effectiveness of the proposed affective model, we use text to simulate and quantify the stimuli first, then compare the emotional arousal of real people and the model under the same conditions. So, the first step is to run a preliminary experiment to determine the model parameters, which can help building the robot affective models for comparison. And in view of the measure of introversion/extroversion being more popular in the current academic research on robot personality [6], we adopt these two personalities as the classification of our sample affective model.

The whole preliminary experiment is conducted through a series of online questionnaires, which can be divided into personality test and stimulus simulation test. The questionnaire material for the personality test is Eysenck Personality Inventory (E Scale) [21]. And the text type materials for stimulus simulation test are selected from the Affective Norms for English Words (ANEW) [18], which contains 718 sentences of 5–23 words, and labeled with emotional valence and emotional arousal. It’s worth mentioning that this data set was evaluated and validated by 148 psychology students from University of Warsaw and 2,091 students from different faculties, in the case of a male-to-female ratio maintaining at 1,030:1,209. Therefore, it fully meets the requirements of authority for the experiments. On this basis, we screen out some representative texts with different levels of emotional arousal from ANEW, then we translate the text and slightly adjust them according to Chinese context to fit our testee in China.

Our testee for the preliminary experiment are 67 people from all over China, who ranges in age from 16 to 80 ($M = 27.01$, $SD = 6.38$). We divide them into 4 groups by age, spaced 10 years apart. And the sample size ratio of these seven groups is 6:45:11:5, sorted from the youngest to the eldest. Besides, there is an equal proportion of men and women in the population, and in the 20 to 29-year-old group, whose sample size is the largest, the ratio of men and women is 22:23.

In the process of the experiment, we publish the questionnaire through the Internet, with controlling the age distribution of the testee. After that each testee will start with the personality test, then read 36 stimulus-texts in turn and rate their emotional intensity of 8 emotions, with the experimental guidance and the self-emotional rehabilitation having completed.

In the first place, we test the reliability and validity of the questionnaire, the result is shown in Table 1.

Table 1. The reliability and validity of the questionnaire.

Item	Reliability		Validity [23]		
Index	Standardized Cronbach's Alpha [22]	CITC for each problem	KMO(p)	Cumulative variance interpretation rate after rotation	Communalities
Value	0.968(>0.7)	<0.49(97%+) <0.40(78%+)	0.659(0.000 < 0.05)	75.452%(>50%)	>0.40(100%)

As seen from the table, the Standardized Cronbach's Alpha shows the results of this questionnaire have excellent consistency and stability, the CITC value shows that each stimulus has a high independence, and the KMO value with p, together with the cumulative variance interpretation rate after rotation and the communalities tell us that the results of the questionnaire are suitable for extracting information. In conclusion, our questionnaire has excellent reliability and validity.

3.2 Calculation of Personality Parameters

Based on the results of questionnaire, we calculate the initial parameters of the loci of control for introverted and extroverted affective model, the detailed process of which is listed as followed:

1. Divide the testee into two groups according to the score of introversion and extroversion, and calculate the mean of each data in each group.
2. Use K-means clustering to estimate a few sets of data that can represent the personality traits of the crowd, with using the mean data in last step as the original cluster center, and the clustering number being two. In this step, both personality and emotional arousal traits are considered, and the final clustering center should be retained.
3. Compare the cluster members in step2 with members of the similar group in step1, and use the mean values of the disputed members and clustering centers to be the final representative data.
4. Correspond the data in step3 to the loci of control according to the emotional arousal value ANEW given.

In the actual process, the ratio of the size of two clusters is 16:19, and there is only one disputed member. The final introverted and extroverted affective model are shown in Fig. 3.

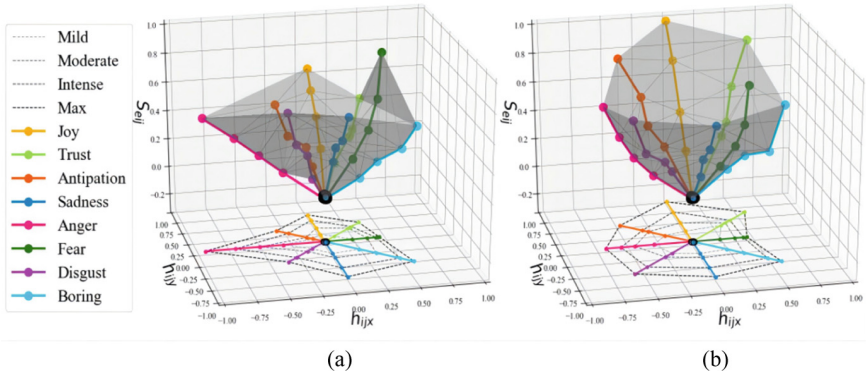


Fig. 3. The introverted/extroverted robot affective models.(a) introverted; (b) extroverted

4 Validation and Evaluation

4.1 Model Test

Based on the introverted and extroverted robot affective models we have built, we can carry out a new round of human-computer interaction experiment, to verify the accuracy of emotion model compared with real human emotion under the same stimulus. In this round of formal experiment, we adopt some online questionnaires with a similar structure to the preliminary experiment. But the difference is that we select texts from ANEW with a new emotional arousal, and we conduct 8 groups of experiments with 25 testee each, categorized according to the category of emotion. The configuration of each group is as follows.

4.2 Results

We use all the texts whose emotional arousal can act as the intensity of input stimulus in the questionnaire mentioned above to prove that our model has a good fit. We feed the stimulus into two emotion models and record the estimated values of the model as e_{es} first. Then by comparing e_{es} with the average observed values in the experiment e_{os} , it can infer that the smaller the absolute value of the difference between the two b , the better the fitting degree of the affective model. The partial results are listed in Table 3.

In the other six emotions, the maximum b are 0.081, 0.124, 0.103, 0.941, 0.065, 0.088, thus it can be seen that our model closely mimicked real people in the emotional expression both introverted and extroverted.

Additionally, we feed the same predefined stimulus to the introverted and extroverted model, while controlling other irrelevant parameters at the same level, to test the difference representation ability of the affective model.

Table 2. The configuration of each experiment group.

Group	Emotion	M_{age}	SD_{age}	Standardized Cronbach's Alpha	KMO(p)
A	Joy	26.28	5.70	0.975	0.723(0.000)
B	Sadness	26.20	5.13	0.801	0.698(0.000)
C	Anticipation	29.08	7.97	0.984	0.602(0.000)
D	Anger	27.76	6.40	0.988	0.649(0.000)
E	Fear	31.00	11.03	0.977	0.601(0.000)
F	Surprise	27.04	7.79	0.959	0.617(0.000)
G	Disgust	29.44	6.82	0.966	0.622(0.000)
H	Trust	27.48	6.62	0.973	0.674(0.000)

Table 3. Comparison of estimated values of affective model with observed values of experiments.

Stimulus intensity		Introverted			Extroverted		
		e_{es}	e_{os}	b	e_{es}	e_{os}	b
Joy	$a_{11} = 2.87$	0.102	0.127	0.025	0.196	0.117	0.079
	$a_{12} = 4.08$	0.231	0.304	0.073	0.311	0.249	0.062
	$a_{13} = 4.25$	0.267	0.279	0.012	0.312	0.339	0.027
	$a_{14} = 4.35$	0.274	0.240	0.034	0.349	0.433	0.084
	$a_{15} = 5.02$	0.398	0.307	0.091	0.447	0.430	0.017
	$a_{16} = 5.75$	0.447	0.508	0.061	0.549	0.571	0.022
	$a_{17} = 6.17$	0.526	0.569	0.043	0.607	0.574	0.033
	$a_{18} = 6.79$	0.607	0.659	0.052	0.729	0.740	0.011
Sadness	$a_{41} = 3.55$	0.279	0.335	0.056	0.191	0.112	0.079
	$a_{42} = 4.10$	0.318	0.399	0.081	0.303	0.334	0.031
	$a_{43} = 4.37$	0.362	0.454	0.092	0.311	0.366	0.055
	$a_{44} = 4.48$	0.373	0.339	0.034	0.351	0.399	0.048
	$a_{45} = 6.07$	0.546	0.621	0.075	0.436	0.360	0.076
	$a_{46} = 6.43$	0.599	0.665	0.066	0.505	0.530	0.025
	$a_{47} = 7.38$	0.670	0.64	0.030	0.551	0.634	0.083
	$a_{48} = 7.46$	0.681	0.728	0.047	0.599	0.647	0.048

It can be seen in Fig. 4. That under the same stimulation, the more explicit emotion include joy, anticipation and trust, will be higher arousal in the extroverted model. Meanwhile, the introverted model shows greater ability to maintain the high level of emotions longer.

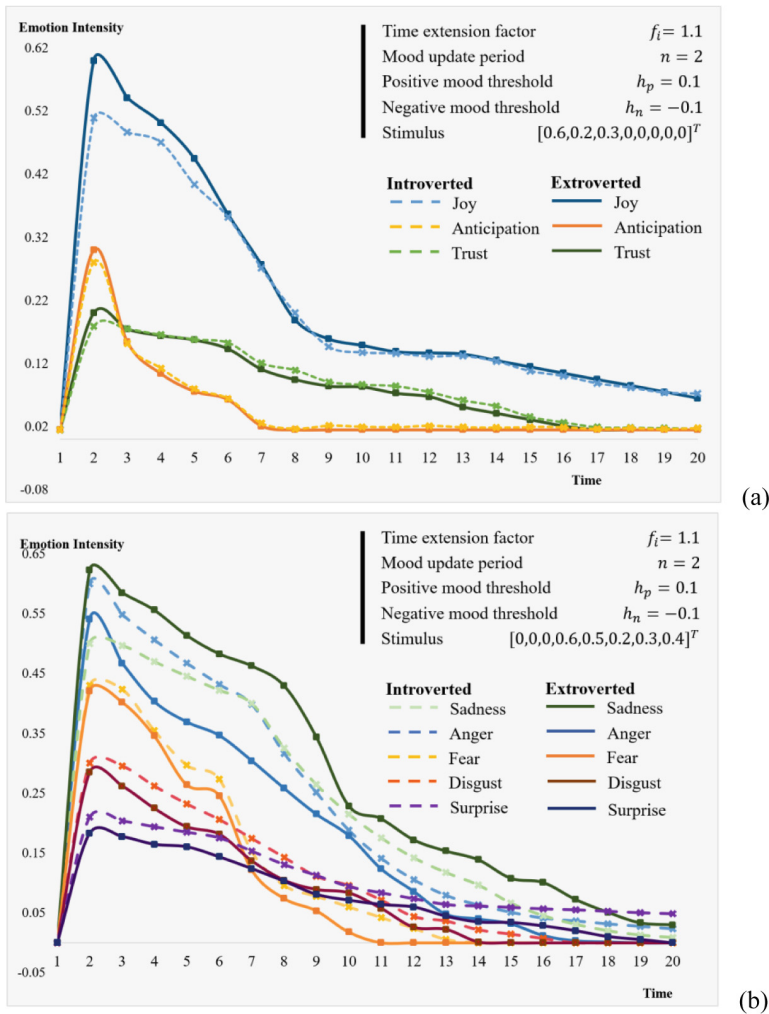


Fig. 4. Comparison of emotion changes under different personality. (a) Positive emotions; (b) Negative emotions.

5 Conclusion and Future Work

In this paper, we have proposed a method for modeling the affective model and personality creation of a 3D social robot based on Plutchik’s Wheel of Emotions, built sample models with introverted and extroverted personalities, and modeled different personalities to broaden the application of the affective model. The findings have been analyzed from questionnaires ratings that were given by 270 individuals of various ages, genders, and personality qualities.

Based on the results of the experiments, the affective model has been preliminarily shown to accurately mimic human multiple personalities, and its affective mechanisms of customized personalities are consistent with humans with the same type of personality.

To further support and confirm our findings, future work such as examining differences in attitudes of people towards robots with and without appropriate personalities in multiple positions can be done. On the other hand, studies based on endogenous emotions in robots concentrate on the behavior of emotional processes acting in people [12], so we will expand our experimental scenarios and consider combining robotic personality mechanisms with behavioral decision-making mechanisms to apply the model to various real-life contexts.

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