Investigation of Perception Towards Robot Expressions Considering Attitude and Personality

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As robots become ever more sophisticated, ubiquitous, and continue to permeate into our everyday life, an important agenda for future studies will be to design and evaluate robots that can adapt its expressions based on user characteristics in real-time and study their effect on perception of the user. To explore the effective expression in human–robot interaction, we intended to endow the humanoid robot Pepper with seven expression patterns showing different combinations of voice and motion traits. The Negative and Anxiety Scale and Big Five Domain Scale were chosen as the psychological indicators, and an online video-based questionnaire was utilized to investigate human perception of robot different expressions. Results have uncovered that robot’s different expressions can elicit individual distinguishing evaluations towards robot. The prominent distinction of personal perceptions among different participants emerges from the data, boosting the idea that the personalized robot with adaptive expression is essential for different individuals and various scenarios. This study provides the first investigations into how to make social robots generate appropriate reactions according to individual inner conditions including personality and attitude towards robots.

Keywords: human–robot interaction (HRI), human perception, negative and anxiety attitudes, personality

1. Introduction and Background

Social robots have become the part of our everyday lives. Research in social robotics has shown its potential impact on numerous applications by assisting people in various scenarios [1]. However, few studies focused on the cognitive, psychological, and social determinants that impact the design of robots’ communication strategies. By providing the evidence of human perception difference, the interdisciplinary study can be an effective tool to promote the development of user-centered design for human–robot interaction (HRI).

A significant challenge obstructing present progress is how to achieve harmonious communication between humans and robots. To address this, more and more research in the field of HRI has focused on adapting the behavior of a robot to the user it interacts with. The adaptation can be based on the personality of the user, the affective state of the user, or different body signals [2–4].

Besides the impact of the mere physical presence of the robot on human in the HRI literature, it emerges that the design of the ways robot’s interact with the users may also affect how people judge its behavior, how they react to it, and their task performance [5–7]. Unraveling human perception of social robots is vital to mapping how people understand others’ mental states, explain as well as predict their behavior, determine the most appropriate behavioral response, and maintain relationships. Such perspectives could prove beneficial in human–robot coordinative mechanisms, which are crucial in supporting more effective and efficient interactions. However, studies among different disciplines have heretofore failed to fully get through mechanisms of human cognition, making robots duplicate the mechanism of the human mind seem hopeless [8].

Additionally, the social signals are perceived as blunted when displayed by a virtual agent, regardless of whether its appearance was realistic or simple [3]. And while parameters allow for sophisticated social expressions, a question emerges as to whether this is necessary, as people are already able to recognize intentional social signals from behavior patterns from a robot [9]. Some research has substantiated that there is a sophisticated relationship between people’s attitudes, personality and emotions toward the robots and their behaviors in the interaction with social robots [10–12]. The research is still insufficient when it comes to deciphering robot’s expressions considering the particular task and individual psychological traits.

Maintaining this emphasis on social robotics places the objective of attaining more natural and automatic interaction at the forefront of our study, with a focus on verbal and non-verbal communicative cues. We also stress that, for more natural and long-term interaction to be possible in HRI, embodied individual perception differences must be taken into account. In this study, considerable attention has been paid to the relationship among one’s personality, attitudes towards robots and how people perceive robots’ expression styles given that the meaningful interaction requires the understanding and integration of those factors. To be more specific, an experiment was performed including videos showing different robot expression styles, and online questionnaire using the Likert-scale method were utilized to explore the influence of the robot expression on human perception. The design of robot expression style is based on different motion (head and arm) and verbal features (pitch and speed). Given the hypothesis that there would be a gap among different individuals’ perception because of personal mental state discrepancy, on one hand, we involved the attitudes scale – Negative Attitudes toward Robots Scale and
Robot Anxiety Scale, which are psychological scales for measuring the mental states of users towards robots with the evaluation of robot expression styles in our study [13, 14]. On the other hand, arose from the evidence that many studies have reported the effect of personal traits including user’s gender, culture, personality, and other psychological features on how they perceive and interpret robots’ expressions during the interaction, we also implement the personality test using the Big Five Domain Scale, in our study to investigate the relationship between personal psychological traits and the perception of the robot [10, 12, 15, 16].

The main contributions of this study can be summarized as follows. We evaluated different robot expression settings pertaining to acoustic and visual information and compared different individuals’ perception combining with individual personality traits and attitudes towards the robot. The experiment is to access the effect of an adaptive robot expression towards richer and more personalized user experience and potential consequences of such an interaction. The goal of this paper is to outline an interdisciplinary and multi-theoretic approach to facilitate the design of social robots that will one day function, and be perceived, as socially interactive and effective partner. The results are beneficial to construct an experimentally solid benchmark for adaptive robot expression design to maintain harmonious HRI in the near future.

2. Related Works

2.1 Robot Expression

The ongoing challenge in developing complex, future and emerging robotics is that of eliciting meaningful information and feedback from users of social robots. From a user-centered design perspective, it is clear that the appropriate expressions can influence the impression of a social robot, the more impact they will potentially have on the interaction. More importantly, the expression signals distinction applies to both robots interpreting humans and humans interpreting robots capable of displaying social cues [17, 18]. Therefore, expanding the utilization of adaptive robots requires further explanation with regard to the dual way in which how humans perceive and react to those signals.

The verbal and nonverbal parameters of social robots allow for sophisticated social expressions, and to show intentional social signals [19]. Verbal communication can be crucial for engagement with humans as it allows for intuitive interaction between humans and robots [20]. On the other hand, in general, nonverbal communication is the unspoken dialogue that creates shared meaning in social interactions which can have emotional or functional intent [21, 22]. For instance, robot body and head movements have been shown to influence human perception of a variety of different concepts including social engagement, intrigue, appeal, warmth, friendliness, empathy, and enjoyment [22, 23].

2.2 Human Perception

Not only robot behavior will affect the interaction process, how people interpret interlocutors’ physical changes through sensory systems is responsible for sustaining the long-term HRI [111]. Exploration of human perception is necessary for effective human–robot coordination and cooperation, as they would afford a user the capacity to interpret robots’ intentions, emotions during socially interactive contexts and support the concurrent display of appropriate behaviors [18].

For delection in the interaction, if the robot can give a reasonable response during HRI, humans will not care if its interior system can obtain a very high accuracy [24]. Some studies have proven that personality adaptation by a social robot could positively impact towards improving user’s task performance and was also able to encourage task performance and attention training, making people enjoy interacting with the robot more [6, 25, 26]. Hence, in addition to improving the algorithms used in the social robots’ detection system, designing a favorable action response of social robots to address the current technological shortcomings is a possible solution.

Furthermore, together with our previous studies, many studies have pointed out that behaviors can be personalized at different levels from physical level to cognitive and social levels taking into account static parameters like user name, gender, personality and dynamic parameters, such as emotion, current response [27, 28]. Research has shown that some people are comparatively more alert to nonverbal cues and better able to identify what those cues mean [29]. The perceptive sensitivity of social nonverbal correlates to personal property and circumstance factors as well.

2.3 Personality in Human–Robot Interaction

Since the need to investigate traits which are more closely tied to the adaptive interaction and cooperation with intelligent robotics has been highlighted, an understanding of individual differences becomes increasingly important, in both human-to-robot and robot-to-human directions [8]. Individual differences which are important to understanding how social cognition differs among populations requires consideration before design of a “one size fits all” robotic partners. However, research focused on the application of individual differences to HRI is scarce.

Personality, as the important internal attribution, affects how people interact with technology. Individual behavior to a social robot is shaped by their personality and impressions. Research has shown that introverted individuals recognized emotions from less visually complex characters better than extroverted individuals [30]. People with different personality perform distinct preference to robot expression, which shows the importance of the adaptive response from robot [31, 32]. Individual differences in perception are beyond our present scope, but they will possibly interact with personality in shaping the person’s interactions with a social robot [2].

In this study, the Big Five model, which is the most widely accepted model of personality, is used for the measurement of participants’ personality traits [16]. It suggests five personality traits: Extraversion (to be sociable, active), Agreeableness (to be soft-hearted, trusting), Conscientiousness (to be organized, reliable), Neuroticism (to be anxious, tense), and Openness (to be curious, creative) [33].

2.4 Attitudes Toward Robots

An attitude is psychologically defined as a relatively stable
and enduring predisposition to behave or react in a certain way toward persons, objects, institutions, or issues, and the source is cultural, familial, and personal [34]. This definition of attitudes implies that they can be affected by cultural backgrounds and personal experiences. Furthermore, based on the idea that changes in attitudes produce a corresponding change in thoughts and behaviors, results also imply that this rule applies to the situation when people interact with robots [35]. Therefore, we believe it is important to further investigate the influences of the features of attitudes and emotions on HRI because personal sentiment and perceptions can shape technology’s assimilation.

### 2.4.1 Negative Attitudes Toward Robots Scale (NARS)

Negative Attitudes towards robots tended to be associated with more negative evaluations of the behavior of robots with Socially Interactive behavior style [13]. This scale consists of fourteen questionnaire items and these items are classified into three subscales: S1: “Negative Attitude toward Situations of Interaction with Robots” (six items), S2: “Negative Attitude toward Social Influence of Robots” (five items), and S3: “Negative Attitude toward Emotions in Interaction with Robots” (three items). The number of grades for each item is five (from 1: I strongly disagree to 5: I strongly agree), and an individual’s score on each sub-scale is calculated by summing the scores of all the items included in the sub-scale, with the reverse of scores in some items. Thus, the minimum and maximum scores are 6 and 30 in S1, 5 and 25 in S2, and 3 and 15 in S3, respectively. The details of the NARS questionnaire are shown in Appendix A.1.

### 2.4.2 Robot Anxiety Scale (RAS)

It is important to measure the anxiety towards robots because solving the problem prevents individuals from alienating interaction with robots in daily life [14]. Robot Anxiety Scale (RAS) was developed to determine human anxiety toward robots evoked in real and imaginary HRI situations. In contrast with the NARS, this scale aims to measure state-like anxiety that may be evoked by robots [14]. This scale consists of 11 questionnaire items classified into three subscales: S1: “Anxiety toward communication capacity of robots” (three items); S2, “Anxiety toward behavioral characteristics of robots” (four items); and S3, “Anxiety toward discourse with robots” (four items). Each item is scored on a six-point scale: from 1: I don’t feel anxious at all to 6: I feel anxious strongly. An individual’s score on each sub-scale is calculated by adding the scores of all items included in the sub-scale. Thus, minimum and maximum scores are 3 and 18 for S1, 4 and 24 for S2, and 4 and 24 for S3, respectively. The details of the RAS questionnaire are listed in Appendix A.2.

### 3. Experimental Setup

With the increasing need for online interaction and the difficulty of owning the robot for all users, it is necessary to use videos to ensure the presentation of social robots engaging in social interactions [36]. While research has reported that participants were more likely to fulfill a task when the robot physically presented than showed in the live video, some studies show no significant differences between these two situations [37, 38]. Furthermore, many studies have achieved considerable results by using videos to represent robots’ different expressions or characters to explore how people evaluate robots [38-40]. Therefore, in this study, an online video-based experiment including a game with a robot and the post-test questionnaire were performed.

A task of spotting differences between two similar images has been chosen considering that it needs one’s short-term attention and can create a relatively natural environment [41]. On the other hand, since it allows various answers according to personal ability and situation, different degrees of confidence can arise which could be used as arousal and emotional stressor [41].

All participants needed to complete 7 sections in the same flow and submit each result of them through Google Form [42]. We recorded videos of a real robot’s performance for the online survey to maximally simulate the real HRI to investigate the perception of robot expression styles in realistic scenarios. The humanoid robot Pepper which was chosen to perform these different expressions because several expected advantages of using the humanoid robot have been verified in social interaction [43, 44]. And some related works of humanoid robot have shown that different impressions of the humanoid robot are due to personal characteristics instead of what specific type the humanoid robot is [44, 45].

To explore relationships among personality traits, attitudes and people’s evaluation towards robots, before the online game, all participants had finished the Big Five Inventory and NARS and RAS questionnaire through Google Form.

### 3.1 Subjects

We recruited 23 participants for this experiment (Female = 8, Male = 15) from our university whose ages ranged from 21 to 29 (M = 24.04, SD = 4.65). Their mother languages are Japanese (N = 12) and Chinese (N = 11), and all of them come from technical backgrounds.

### 3.2 Robot Expression Design

Seven patterns of robot expression have been utilized going with seven sections in this experiment to investigate human perception of the robot. We use positive and negative states to differentiate the expression styles as they are the general standard for designing robot behaviors [46]. The differences between the negative and positive states include the variation of speech tone and speed and different movements. Given the consequences that people feel a robot weird when the emotional states of verbal and motion feature are contrary, for example, when the robot’s motion was designed as the positive image but its verbal feature is set as the negative one (a low tone or discouraging utterance), to avoid such cross-impact we didn’t use the opposite motion and verbal attributions in this study [47]. The corresponding connection of section number and expression style which was decided by random function is described in Table 1. The demonstration of robot different motion styles is shown in Fig. 1 and details of robot verbal and motion traits are listed in Table 2. Each expression was
3.3 Experimental Procedures

Before the first section, participants needed to fill in their basic personal information including name, gender, mother language and whether they have the interaction experience with a robot or not, and then the participants finished the task in which they watched several short videos presenting the robot Pepper with the whole body part in default voice and motion settings. After finishing the first section as the control condition to make participants be acquainted with the basic state of the robot, participants were asked to finish the left sections in a random sequence to avoid order bias.

In the first section, a video firstly showed the robot greeting with the participant, introducing the details of the spot difference game, and explained to the participant what they had to do in the experiments. The following game process was shared in all 7 sections. After preparing to concentrate on the game, each participant was allowed to move to the part to observe each pair of images showing on the computer screen for utmost 1 minute to find the differences between them as much as possible. They were forbidden reviewing the images after the observation time. Then the participant needed to watch a video showing the robot asking how many differences have been found and needed to answer by selecting the number ranged from 0 to 3 or the selection of greater than 4. We didn’t set an accurate upper limit to avoid the potential influence on participants’ confidence of their original answers. Afterwards, the online questionnaire would jump to one video showing the robot saying comforting words, saying: ‘That’s great,’ and the participant would be led to another video showing the robot asking whether the participant was confident about her/his answer or not. Similarly, to keep robot’s responses natural enough, after selecting if he or she was confident about the found difference number, if the participant felt confident, the online questionnaire would jump to one video showing the robot with complimentary response, saying: ‘You’ve done a great job,’ while the unconfident selection would lead to another video showing the robot with encouraging response saying: ‘Don’t worry, your answer could be right.’ Finally, in the last part of each section, each participant needed to fill in a questionnaire which was composed of the impression and likability towards the robot, the enjoyment of the game demonstrated in this section, the confidence degree about the answer measured on a scale from 1 to 7, and the game difficulty assessment based on subjective feeling measured the scale from 1 to 5. We set the last two questions to collect participants’ evaluations of the spot difference game in each section for the purpose of excluding the potential influence of the task performance on evaluations of the robot. The details of the post-experimental questionnaire are shown in Table 3. Not until all seven sections had been finished, would participants be guided to an unfinished section with the same procedure. In section interval, the participants could have a rest whenever they needed. A video illustrating the robot said thanks and gave farewell was shown after the last section had been finished. The whole online experimental process is depicted in Fig. 2.

4. Results and Discussion
4.1 Attitudes and Anxiety Scale

Analysis of Standard Deviation and a between-subjects calculation of Pearson correlation coefficient were conducted on attitudes and anxiety questionnaire results. The results shown in Table 4 manifests the statistical results. A significant correlation between the S1 sub-scale in Robot Anxiety Scale (RAS-S1) and participants’ mother language has been uncovered. To be specific, the participant whose mother language is Chinese felt less anxious about communication capacity of robots. However, except for this factor, participant gender, language (Japanese, Chinese), were found to be non-significant correlated with other scales and thus will not be further discussed in this paper.

4.2 Online Questionnaire

For the online questionnaire, Pearson correlations coefficient between the results of each pair of two questions and personal traits have been calculated. However, no significant differences have been presented for different gender and mother language groups this time. Given the commonsense, results of a negative correlation between the evaluation of confidence degree and game difficulty as well as the positive correlation between likability towards robot and enjoyment in all sections will not be discussed.

According to the correlation results in each section, the evaluation of positive image of robots is always positively correlated with people’s Likability verifying the idea that participants prefer
Table 3  Details of online questionnaire

| No. | Question Content                                                                 | Shorten Version | Answer Choice                                                                 |
|-----|----------------------------------------------------------------------------------|----------------|-------------------------------------------------------------------------------|
| 1   | The impression of the robot in this section is positive                          | Positive Identity | 1 – “I disagree completely”; 7 – “I agree completely”                        |
| 2   | I think the robot in this section is favorable                                    | Likability      | 1 – “I disagree completely”; 7 – “I agree completely”                        |
| 3   | I enjoy the game with the robot in this section                                  | Enjoyment       | 1 – “I disagree completely”; 7 – “I agree completely”                        |
| 4   | I am confident that I have found out all differences (if has) between two images in this section | Confidence | 1 – “I disagree completely”; 7 – “I agree completely”                        |
| 5   | The difficulty of the spotting differences game in this section                  | Difficulty      | 1 – “easy”; 5 – “difficult”                                                  |

To explore human perception towards different expression styles, we horizontally compared the results from each section. Fig. 3 illustrates the Box and Whisker charts based on each question results in the online questionnaire. The plots of positive identity, likability of robot and enjoyment of the game altogether show that participants evaluate section 3 which shows the robot with positive motion and positive voice traits as the most favorable and section 2 which shows the robot with negative motion and negative voice traits as the least favorable. Meanwhile, section 4 which shows the robot with negative motion and normal voice traits and section 5 which shows the robot with positive motion and normal voice traits show exactly the same results in each question. Similarly, in section 2 which shows the robot with negative motion and negative voice traits and section 6 which shows the robot with normal motion and negative voice traits evaluations are kind of close. On the other hand, there are quite apparent differences between the results in sections 6 and 7 in which the robot showed same motion traits but different voice traits. The result has shown that participants could basically figure out voice changes, enjoyed the game more and evaluated the robot with a positive voice more favorable. The distinguishing distinction of voice changes and similar evaluation of motion differences have presented that most participants are more sensitive for robot’s voice features but less sensitive towards robot motion features.

However, individual differences have also shown. The results from section 3 which shows the robot with positive motion and a robot with a positive image. At the same time, results have revealed that either the participant’s confidence degree or the difficulty evaluation of the game itself doesn’t influence participants’ likability towards the robot and their enjoyment of the game. No other statistically significant correlation has been shown among other aspects.
positive voice traits and section 7 which shows the robot with normal motion and positive voice traits are assessed very similarly in positive identity, likability and enjoyment, the plots have shown that clearly, compared to that of section 7, the results of section 3 distributes in a wider range which have uncovered individual perception and preference differences towards robot’s expressions.

4.3 Relationship Between Attitudes and Anxiety Towards Robot and Questionnaire Results

According to the analysis of Pearson correlation between each answer in the questionnaire and NARS and RAS, the positive identity and likability towards robot in section 2 which showed the robot with negative motion and negative voice traits have shown distinguishing negative correlation with RAS-S1 which measures the anxiety toward communication capacity of robots. The statistical results are listed in Table 5. Meanwhile, the results of either only voice or motion being negative haven’t shown any significant correlation with this aspect, exposing the fact that the participant who feels more anxious about robot communication ability is also more perceptive of the robot showing negative motion and negative voice simultaneously and tends to evaluate it as more unfavorable. However, no other significant correlation between attitudes and anxiety towards robot and questionnaire results has been shown in other sections.

| Measurement traits | Pearson correlation | RAS-S1 |
|--------------------|---------------------|--------|
| Positive Identity  | −0.70***             |        |
| Likability         | −0.79***             |        |

***p < 0.001

4.4 Relationship of Personality Traits and Questionnaire Results

Although related works have explored the relationship between people’s personality and their attitudes towards robots (NARS and RAS score), in this study, there isn’t significant correlation between any item of NARS and RAS and participants’ Big Five traits according to the results of Pearson correlation coefficient. The limited number of participants may cause the consequence. However, according to our previous research, the individual traits including personality and perception have shown more distinguishing influence on one’s interaction with a robot.

For the purpose of exploring the relationship of participants’ attitude towards robots that are measured by the NARS and RAS questionnaire, the personality measured by Big Five traits and the perception of the social robot which is represented from the online questionnaire results in our research, except for calculating Pearson correlation coefficient between participants’ Big Five traits and the results of each question, the differences of the evaluation score of each question between every two sections by means of subtracting the Likert-scale score of one question to the corresponding one have also been conducted. In this way, the connection of different individual’s perception of robot’s voice and motion traits and one’s internal features including attitude and personality could be revealed.

After calculating the Pearson correlation coefficient between the differences of scores of each section and participants’ Big Five traits, although neither showed strong or moderate correlation, some consequences have intrigued our attention. We have analyzed the characteristics of the section where Pearson correlation coefficient is relatively high. From the differences of the evaluation of likability in section 1 which exhibited the robot with normal voice and normal motion traits and section 3 which showed the robot with positive motion and positive voice traits as well as that in section 7 where the robot showed normal motion and positive voice traits, we have noticed that participant who has lower Openness score evaluated the robot with normal
voice and normal motion traits as more favorable than that with positive voice. It is interesting to note that no matter the robot showed positive or normal motion traits, participants with the lower Openness score tended to dislike the robot with positive voice traits. Since we didn’t set the section showing the combination of the positive voice and negative motion traits, the negative correlation between the Likability of the robot and Openness is probably caused by robot’s positive voice traits. Fig. 4 depicts the consequence aforementioned.

Furthermore, according to the analysis of the evaluation of the enjoyment in section 2 which showed the robot with negative voice and negative motion traits and section 4 which showed the robot with normal voice and negative motion traits as well as that in section 5 which showed the robot with normal voice and positive motion traits, it has been uncovered that the participant who has lower Conscientiousness score evaluated the interaction with the robot showed negative voice and negative motion traits as more enjoyable than that with normal voice regardless of the state of its motion. In other words, the participant with lower Conscientiousness enjoyed the interaction with the robot which displayed negative voice traits. Fig. 5 illustrates the relationship of one’s Conscientiousness score and the higher score of Enjoyment evaluation with the comparison between section 2 and section 4 or 5. These results have provided evidence that the personality traits could affect particular individual’s perception towards the robot’s expressions.

4.5 Discussion

As revealed in the relationship between the RAS-S1 score and evaluation of the robot with negative motion and voice expression, there is a statistical trend toward a significant effect of anxious attribution: the more the participants estimated the communication capacity of robot as being anxious, the lower scores of the likability they evaluated the robot. It is supposed that negative expression combining motion and voice has incurred the participant’s anxiety strongly who shows more intensive anxiety towards the robot’s communication capacity. Considering the results that no significant differences have been exhibited when robot merely expressed with negative voice or negative motion, the higher RAS-S1 score is not corresponding to be more sensitive to a single dimension of the negative features but the combination of them.

Besides, unlike the general division way of groups such as the gender and nation differences, except for a relationship between one’s mother language and RAS-S1, the results of NARS and RAS scores have shown significant personal variation. In our previous studies, the individual traits including personality and perception have shown more distinguishing influence on one’s interaction with a robot instead of gender and mother language [12,48]. Therefore, the consideration of specific individual situation instead of the typical labels is indispensable.

Moreover, from the differences of the evaluation of Positive Identity between the results of section 1 which exhibited the robot with normal voice and normal motion traits, section 6 which showed the robot with negative voice and normal motion traits as well as section 7 in which the robot displayed the positive voice and normal motion traits, and that in section 2 in which the robot displayed the negative voice and negative motion traits respectively, it is observed that participant who has higher RAS-S1 score evaluated the robot with negative motion traits much less positive. The consequence has verified the idea that the participant who feels more anxious about robot communication ability is also more perceptive of the robot showing negative motion thus tends to evaluate the robot less favorable. Table 6 demonstrates the Pearson correlation coefficient between RAS-S1 score and the section where showed higher score of Positive Identity compared to section 2, meanwhile Fig. 6 shows the relationship of one’s score of RAS-S1 scale and the higher score of Positive Identity evaluation drawing the comparison between sections 2 and 6. Further exploration of the function of personal traits including attitudes and personality in HRI is highly anticipated for the design of adaptive robot expression style.

5. Limitation

The study has several limitations which call for future research. Firstly, this study is limited by a relatively small number of participants. Secondly, because the online experiments in-
Table 6  The relationship between RAS-S1 score and positive identity

| Section with Higher Score comparing to section 2 | Pearson correlation |
|-----------------------------------------------|---------------------|
| 1                                             | 0.52*               |
| 6                                             | 0.59**              |
| 7                                             | 0.58**              |

*p < 0.05, **p < 0.01

Fig. 6  The relationship of RAS-S1 scale and positive identity

The results show a sophisticated relationship between one’s Openness and Conscientiousness traits and their perception of the robot’s voice trait than motion trait but inevitably differ from the real HRI and limited participants from the same subject background have been selected in this experiment, it is not yet possible to conclude that the results are applicable to all situations and all kinds of people. Future studies are expected to expand the representative sample and utilize a greater variety of expression styles on different robotic platforms.

Our goal, however, was not to find users’ general preferences for certain design factors, but to examine how people categorize and make sense of design features for social robots, particularly in relation to existing design frameworks from the field. We suggest this more active role of participants in HRI would provide us with useful insights to find other possibilities for social robot design, and help researchers envision more diverse functions of social robots.

6. Conclusion and Future Work

We have conducted an online questionnaire experiment presenting a humanoid robot with different expressions based on voice and motion changes to collect people’s feedback, intending to find the corresponding relation among the sensory profile of the individual including personality traits, perception and attitudes towards robots.

Results have shown that generally, most participants are more perceptive about the robot’s voice trait than motion trait but individual differences are shown. Moreover, the analysis of personality, attitudes and the evaluation of the robot has revealed that anxiety of the communication capacity is significantly related to the perception of the robot with negative motion and voice. Furthermore, for the targeted goal, personality traits have been integrated with the evaluation of robot expressions in which results show a sophisticated relationship between one’s Openness and Conscientiousness traits and their perception of the robot’s voice features. The discrepancy of the results of the attitudes and personality traits implies that robotics design must take account of individual differences instead of only conforming with the average level as the criterion. Nevertheless, the present study offers promising evidence that customizing social robots’ behavior might be crucial to construct the valid robot expressions for different individuals in HRI which can motivate predictive responses based on users’ perception and psychological traits. Due to the characteristics of the experiment design in this study, it is promising to apply those consequences into more situations, especially the educational scene where the utilization of robots is increasingly getting more attention.

We plan to conduct a follow-up study including more exploration of individual-based factors relating to one’s perception of the robot by measuring human behaviors and feelings in the interaction with robot, aiming to facilitate the natural social interaction without the distraction of trivialized and unnecessary actions.

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Appendix A: Negative and Anxiety Scale

A.1: Negative Attitudes Toward Robots Scale (NARS)

| Subscale | Questionnaire Items |
|----------|---------------------|
| S1       | I would feel uneasy if I was given a job where I had to use robots.  
          | The word “robot” means nothing to me.  
          | I would feel nervous operating a robot in front of other people.  
          | I would hate the idea that robots or artificial intelligences were making judgements about things.  
          | I would feel very nervous just standing in front of a robot.  
          | I would feel paranoid talking with a robot. |
| S2       | I would feel uneasy if robots really had emotions.  
          | Something bad might happen if robots developed into living beings.  
          | I feel that if I depend on robots too much, something bad might happen.  
          | I am concerned that robots would be a bad influence on children.  
          | I feel that in the future society will be dominated by robots. |
| S3       | I would feel relaxed talking with robots.*  
          | If robots had emotions I would be able to make friends with them.*  
          | I feel comforted being with robots that have emotions.* |

(*Reverse item)

A.2: Robot Anxiety Scale (RAS)

| Subscale | Questionnaire Items |
|----------|---------------------|
| S1       | Robots may talk about something irrelevant during conversation  
          | Anxiety toward Communication Capability of Robots  
          | Conversation with robots may be inflexible  
          | Robots may be unable to understand complex stories |
| S2       | How robots will act  
          | Anxiety toward Behavioral Characteristics of Robots  
          | What robots will do  
          | What power robots will have  
          | What speed robots will move at |
| S3       | How I should talk with robots  
          | Anxiety toward Discourse with Robots How I should reply to robots when they talk to me  
          | Whether robots understand the contents of my utterance to them  
          | I may be unable to understand the contents of robots’ utterances to me |

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