Personality Traits Assessment using P.A.D. Emotional Space in Human-robot Interaction

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Abstract: Cognitive social robotics is the field of research that is committed to building social robots that facilitate to draw parallels with human beings. Humans assess the behavior and personality of their counterparts to adapt their behavior and show empathy to flourish human-human interaction. Similarly, assessment of human personality is highly critical in realizing natural and intelligent human-robot interaction. Numerous personality traits assessment systems have been reported in the literature; however, most of them target the *big five* personality traits. From only visual information, this work proposes to use pleasure, arousal, and dominance emotional space for the assessment of personality traits based on the work of Mehrabian. To validate the system, three different scenarios have been developed to assess 12 different personality traits on a social humanoid robot. Experimental results show that the system can assess human personality traits with 84% accuracy in real-time and, hence, it can adapt its behavior according to the perceived personality of the interaction partner.

1 INTRODUCTION

With the technological advent and constant research in the field of robotics, it is now quite practical to acknowledge the actuality of social robots being a part of human's daily life in the next decades. It necessitates and inspires the motivation of creating robots that can perceive the various learnings of life similar to humans, especially in a real-world Human-Robot Interaction (HRI). Concerning HRI, the basic expectations from a social robot are to perceive words, emotions, behaviors, and so on, in order to draw several conclusions and informed decisions for realizing natural HRI. Henceforth, assessment of human personality traits is essential to bring a sense of appeal and acceptance towards the robot during the interaction.

Personality plays a vital role in Human-Human Interaction (HHI) as it guides the conversation towards a level of satisfaction and comfort for humans. According to psychologists, human behavior is known to be a combination of verbal cues together with nonverbal cues. Nonverbal cues such as temperamental characteristics are known to be innate in human beings, sometimes existing subtly or visibly. These temperaments aggregate into traits, e.g., extrovert or introvert, throughout human life through daily experiences. The significance of personality in HHI can be better exemplified by two renowned theories from the field of human psychology, i.e., the chameleon effect (Chartrand and Bargh, 1999) and similarity/attraction theory (Henderson and Furnham, 1982). The chameleon effect explains the non-conscious human tendency to passively mimic the behavior of one's interaction partner in a social environment.

In contrast, the similarity/attraction theory emphasizes that humans are generally attracted to and prefer the company of others who maintain morals and attitudes similar to their own. For example, it is quite often observed that there exists a sense of shared personality among friends than among random pairs of strangers. People tend to change their behavior according to their interlocutor's behavior. If he/she is talkative and expressive, one also tends to be more expressive. Therefore, assessment of human personality is highly crucial for a robotic system in order to interact and adapt naturally for intelligent HRI.

The primary goal of this work is the assessment of human personality traits in the real-world using the temperament framework presented by Mehrabian (Mehrabian, 1996). The author has exploited the pleasure, arousal, and dominance emotional space to describe and measure individual differences on different personality scales. This work formulates a hypothesis that *using P.A.D. emotional space, computed through human nonverbal cues, can provide a successful assessment of human personality traits*

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in the context of HRI. To realize the hypothesis, P.A.D. dimensions are computed using nonverbal cues, namely, human posture, head gesture, hand gesture, proximity, body activity, and facial expression. These P.A.D. values are then used in different personality trait equations devised by Mehrabian (Mehrabian, 1996) for assessment of personality traits.

2 LITERATURE SURVEY

There are many complex models available in psychology to recognize the personality traits of humans. The most significant theory that describes personality traits in five dimensions is commonly known as the big five (BF) personality theory or five-factor model. Costa and McCrae (Costa Jr and McCrae, 1976) have introduced the BF model, which is based on five dimensions, namely, extroversion, agreeableness, neuroticism, conscientiousness, and openness to new experiences. Each dimension is a continuum, and a low value in the dimension represents the opposite characteristics of that dimension.

Some researchers have tried to map the cognitive emotional models directly from humans to a robot, for example (Rodić et al., 2016). However, conventional approach is to use personality models from psychology. The BF model has been used extensively in the literature of personality traits assessment. In the case of automatic personality detection from nonverbal behavioral cues, authors (Batrinca et al., 2011) have applied automatic detection of the BF personality traits in scenarios of self-presentation and employment interviews. Different features, 17 visual, 3 speech time, and 9 acoustic cues have been used for classification. The visual nonverbal cues include eye-gaze, frowning emotion, hand movements, head orientation, mouth fidgeting, and posture.

In their further work, authors (Batrinca et al., 2012) have explored to detect the BF personality traits in the human-computer interaction scenario using the map task. The work aims to recognize the BF personality traits in a collaborative task setting. Features used for classification of personality traits are acoustic features, e.g., duration of speech, pitch, intensity, and so on; visual features, e.g., motion vector magnitude over skin computed by using discrete cosine transform, and additional features such as the number of speaking turns by the subject. Authors have used support vector machines (SVMs) for the classification task. The results report an accuracy of greater than or equal to 70 percent for emotional stability, extroversion, and conscientiousness scales. Although authors have argued having detected the BF traits accurately except for open to new experiences trait, a question that remains unanswered is how the lack of features, for instance, the distance between the speakers, detection of facial expression, and many more have been compensated.

Interesting research on the automatic analysis of engagement in HRI is observed in the findings by (Salam et al., 2016). This work aims to judge the impact of personality traits of human participants on the engagement with robots. Among the three phases of analysis, the first phase consisted of data collection in the HRI triadic scenario, while the second phase included extraction of individual and interpersonal features based upon nonverbal cues from human participants. Individual features include a histogram of gradients (HOG), a histogram of optical flow (HOF), body activity, joint speed, motion features, etc. Interpersonal features include the visual focus of attention, the global quantity of movement, relative orientation, and distance between the participants, and relative orientation with respect to the robot. The final phase included a prediction of the level of engagement in two types of engagement, namely individual and group engagement, based upon the predicted the BF personality traits and the features extracted in phase 2. They have concluded that the prediction of engagement using personality traits reports better results as compared to when personality trait information is not used.

In the context of HRI, authors (Zafar et al., 2018a) have presented a humanoid robot that can recognize 3 dimensions of the BF model in real-time. The authors have discussed the importance of nonverbal cues in automatic personality recognition. Nonverbal features such as human postures, facial expressions, body activity, head gestures, and proximity have been used. SVMs are used for the classification task. Authors have claimed above 90% recognition rate for 3 dimensions, namely, extroversion, agreeableness, and neuroticism.

The works mentioned above for personality assessment are directly based on either visual features or linguistic features or both of them. They also are focused mainly on BF personality traits. However, Mehrabian has presented a general framework for describing and measuring individual temperaments of personality that also covers more traits, such as shyness, anxiety, and aggression (Mehrabian, 1996). This framework is based on pleasure, arousal, and dominance emotional space (Russell and Mehrabian, 1977). After extensive research, authors have defined these three domains as follows. Pleasure can be determined using cognitive judgments of evaluation, i.e., higher evaluations of stimuli associated with greater pleasure induced by stimuli. Arousal corresponds to judgments of high-low stimulus activity using measure of stimulus “information rate”. Dominance is defined as judgment of stimulus potency, with more significant the influence of stimuli corresponding to lower values of dominance.

To the best of our knowledge, there exists no research that has implemented the framework (Mehrabian, 1996) on human personality traits concerning the adaptivity and behavior of social robots in HRI. Our work is the first to implement this psychology framework for human personality traits assessment using nonverbal cues in the context of HRI.

3 PERSONALITY TRAITS ASSESSMENT

Although a limited number of technical systems have been reported in the literature for real-time personality traits assessment, these systems at best can *only* recognize the BF personality traits. They are unable to distinguish between subtle personality traits, for example, shyness and introversion or dominance and aggression. According to (Watson and Clark, 1997), extroversion can be subdivided into the more specific facets of assertiveness, gregariousness, cheerfulness, and energy. Similarly, neuroticism can be subdivided into loneliness, anxiety, and sensitivity to rejection, while shyness is the part of introversion trait. As mentioned in the previous section, this work employs the framework (Mehrabian, 1996) that uses pleasure, arousal, and dominance (P.A.D.) emotional space for personality traits assessment. In the following subsection, P.A.D. emotional space is defined.

3.1 P.A.D. Emotional Space

In literature, human emotions are often defined in multiple dimensional spaces. However, the definition of emotion varies for each researcher, who adopted one or more dimensions to define it. For example, according to (Wundt and Judd, 1897), the three dimensions of emotions are namely, “pleasurable vs. unpleasurable”, “arousing vs. subduing” and “strain vs. relaxation”. Many emotional spaces have been presented in psychology. Among them, the prominent ones are the circumplex model by Russell (Russell, 1980) and the Positive Activation-Negative Activation (PANA) model (Watson and Tellegen, 1985).

There exists another renowned three-dimensional emotional space, called Pleasure-Arousal-Dominance emotional space (Russell and Mehrabian, 1977). The P.A.D. model aims to describe and measure emotional traits that correspond to human personality. The three dimensions are defined to be bipolar such that pleasure is described as a continuum that ranges from intense pain or unhappiness on one end to intense happiness or ecstasy on the other. Arousal has been reported to range from sleepiness and drowsiness to a high level of alertness and excitement. Dominance varies from emotions of a complete absence of control or impact over events to feeling influential and in control of the situation at the opposite extreme. In the following sections, a methodology that uses nonverbal cues for the implementation of P.A.D. emotional space is presented.

3.1.1 Pleasure

As previously mentioned, the value on the pleasure scale describes how much the event is enjoyable for a person. The study on facial expressions conducted by (Boukricha et al., 2009) shows that pleasure is directly associated with facial expressions. If a person is happy, the value on the pleasure scale is high. Similarly, if a person is unhappy and exhibits facial expressions such as sadness, fear, anger, or disgust, then the value on the pleasure scale is low.

Algorithm 1: Estimation of Pleasure Value.

```
pleasant = 0, unpleasant = 0
n ← number of frames in 10 seconds
for i ← 0 to n do
    if Human.Face.Exist() then
        P_expression ← Current.Expression
        if P_expression = happy OR surprise then
            pleasant = pleasant + 1
        else
            unpleasant = unpleasant + 1
if pleasant ≥ unpleasant then
    P ← pleasant
else
    P ← unpleasant × (−1)
pleasure = (1/n) × P        // average pleasure
return pleasure
```

To estimate the pleasure value from facial expressions, a system developed by authors (Al-Darraji et al., 2017) has been used to recognize six basic facial expressions in real-time. The facial expressions, extracted in every frame, are standardized and averaged over a 10 second period. Happiness and surprise expressions contribute towards the positive value of pleasure scale, while sad, fear, disgust, and anger contribute towards the negative value of pleasure scale.

Algorithm 1 shows the estimation of pleasure.

3.1.2 Arousal

The value on the arousal scale describes how much the event is exciting and thrilling for a person. The arousal can be assessed by the combination of two nonverbal features, namely proximity and body movements. According to (Nass and Lee, 2001), people, when aroused, show frequent body movements. Similarly, (Hirth et al., 2011) have established the relationship between the proximity of a person from the interlocutor and the arousal. Arousal of a person is considered high if he/she moves towards or stands close to the robot. If a person moves away or stands farther from the robot, the arousal value goes down. To calculate arousal value, a weighted sum of proximity and body movements is used. In order to estimate the proximity value, the concept of interpersonal distances of humans during human-human interaction has been used. According to (Hall, 1963), interpersonal distances of a person can be categorized into four zones, namely intimate space, personal space, social space, and public space. If the robot is in the public space of a person, the proximity value is negative -1. If the robot is in the intimate space of a person, the proximity value increases up to $+1$.

To detect human body movement during interaction, skeleton joints positions of the upper body are used, which are provided by the NiTE middleware library and analyze them over time. Activity is detected if the change in values is exceeded from a threshold. The proximity of a person with regards to a robot is determined by using the depth information of tracked humans. Equation 1 shows the weighted summation of activity and proximity to estimate arousal.

$$Arousal = \frac{1}{n}\sum_{i=0}^{n}(W_p \times P + W_A \times A)$$

$$\left.\begin{aligned} W_p &= 0.8 \\ W_A &= 0.2 \end{aligned}\right\} \qquad \triangle P > 0.5m$$

$$\left.\begin{aligned} W_p &= [0.6-0.8] \\ W_A &= [0.4-0.2] \end{aligned}\right\} \qquad 0.2m < \triangle P \leq 0.5m \qquad (1)$$

$$\left.\begin{aligned} W_p &= 0.6 \\ W_A &= 0.4 \end{aligned}\right\} \qquad \triangle P \leq 0.2m$$

In Equation 1, W_p and W_A are proximity and activity weights, respectively. The weights are dynamic and change according to the change in proximity, $\triangle P$, of a person. If a person moves more than half a meter during the interaction, the W_p gets the higher value to depict this sudden change on the arousal dimension. Moreover, the proximity value (P) is a continuous value between -1 to $+1$ and depends on how far the person is standing from the robot.

3.1.3 Dominance

In the HRI scenario, dominance can be estimated by analyzing human behavior over time. As mentioned by (Jensen, 2016), confident and dominant people generally have a wide-open trunk during interactions, which shows that they are approachable to others and keeps them in a more open-minded attitude. Similarly, threatening postures such as feet spread apart with hands-on-hips posture and pointing postures are correlated with aggression and dominance. Dominant people are also physically active during interactions. In contrast, submissive people tend to look down with slumped body postures. Submissiveness is correlated with self-touching postures, such as cross arms posture or thinking postures (Argyle, 1988). Submissive people also avoid mutual eye gaze (Argyle, 1988). They generally are passive during interactions.

The system developed in (Zafar et al., 2018b) has been used to recognize different human postures us-

Algorithm 2: Estimation of Dominance Value.

```
dominant = 0, submissive = 0
n ← number of frames in 10 seconds
for i ← 0 to n do
    if Human.Body.Exist() then
        P_posture ← Current.Posture
        P_head_gesture ← Current.Head_Gesture
        P_body_movements ←
          Current.Body_Movement
        if (P_posture = O.P OR P.P OR A.S) AND
          (P_head_gesture = L.A OR L.U) AND
          (P_body_movements = true) then
            dominant = dominant + 1
        else if (P_posture = C.P OR T.P) AND
          (P_head_gesture = L.D OR L.A OR L.L
          OR L.R) AND
          (P_body_movements = false) then
            submissive = submissive + 1
        else
            do nothing
if dominant ≥ submissive then
    D ← dominant
else
    D ← submissive × (−1)
dominance = (1/n) × D   // average dominance
return dominance
```

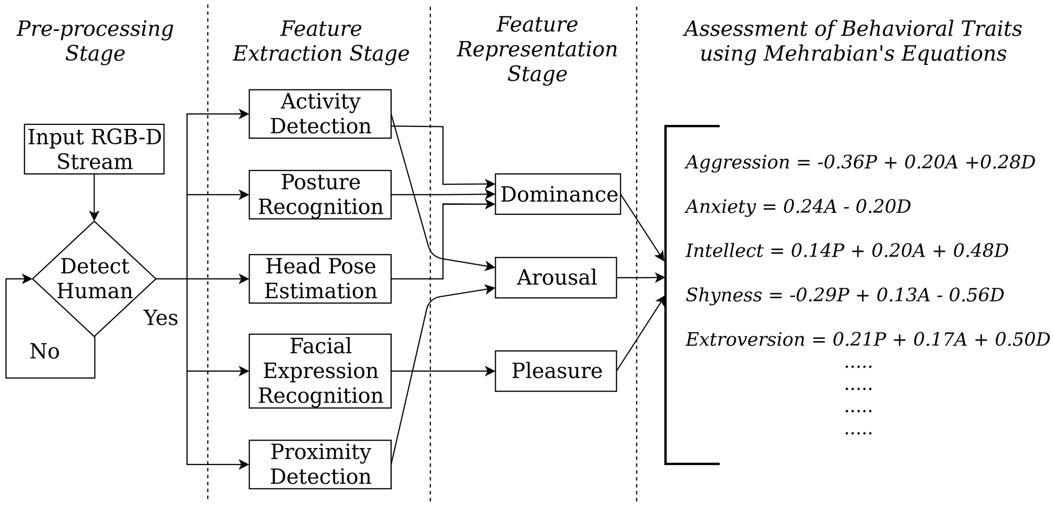

Figure 1: Schematic flow of personality traits assessment using P.A.D. emotional space from findings of (Mehrabian, 1996).

ing human skeleton joint angles, e.g., pointing posture, thinking posture, crossed arms posture, open arms posture, aggressive posture and so on. To recognize head gestures, the system developed in (Saleh and Berns, 2015) has been used. Head gestures such as head nodding, head shaking, look left, look down, look up, look right, look ahead, etc. are considered in this study. Body movements of a person are detected using the same method described in Arousal implementation. Algorithm 2 shows the estimation of the dominance dimension.

In Algorithm 2, O.P = open posture, P.P = pointing posture, A.S = Aggressive stance posture, C.P = crossed arms posture, T.P = thinking posture, L.A = looking ahead gesture, L.U = looking up gesture, L.D = look down gesture, L.L = look left gesture and L.R = look right gesture.

3.2 Personality Trait Assessment System

This work proposes to use the P.A.D. emotional space for the assessment of human personality traits using the Mehrabian's framework (Mehrabian, 1996). Using the three dimensions, pleasure, arousal, and dominance, he has formulated 59 individual measures that correspond to human personality traits. It has been demonstrated that traits are symmetrically related to one another based upon the P.A.D. dimensions.

Although the formulated traits are of a wide range, only 12 out of 59 traits are realized in this work. These traits are chosen according to the experimental restrictions and based on the knowledge of nonverbal cues associated with them. Personality traits such as mysticism, loneliness, and anorexic require either verbal or contextual information or both for an accurate assessment. Furthermore, even humans find it challenging to assess these traits in human-human interaction. Therefore, 12 realizable traits are considered. These traits' equations, which are reported in (Mehrabian, 1996), are shown in the Equation 2. Figure 1 shows the schematic flow of the approach.

$$
\begin{aligned}
Intellect &= 0.14P + 0.20A + 0.48D \\
Achievement &= 0.13P + 0.60D \\
Extroversion &= 0.21P + 0.17A + 0.50D \\
SocialDesirablility &= 0.34P - 0.26A + 0.17D \\
ArousalSeeking &= 0.14P + 0.26A + 0.55D \\
Aggression &= -0.36P + 0.20A + 0.28D \\
TraitDominance &= 0.72D \\
PhysicallyActive &= 0.26P + 0.40D \\
Anxiety &= 0.24A - 0.20D \\
Shyness &= -0.29P + 0.13A - 0.56D \\
SensitivitytoRejection &= 0.14A - 0.71D \\
Nurturance &= 0.41P + 0.12A + 0.17D
\end{aligned} \tag{2}
$$

4 EXPERIMENTATION

The main hypothesis proposed is that the use of P.A.D. emotional space, computed through human nonverbal cues, can provide a successful assessment of human personality traits in the context of HRI. Due to the unavailability of ground truth, the validation of the hypothesis is a challenging task. In order to validate the authenticity of the proposed system, written feedbacks have been compiled in the form of a questionnaire from psychology students. In the following sub-sections, the experimentation and evaluation procedure is described in detail.

4.1 Experimental Setup

For experimentation purposes, 15 university students (12 males, 3 females; age range 22-45 years) from different ethnical backgrounds have participated. The participants have been naive about the objective and nature of the experiments. The participants provide informed consent with regards to the guidelines of an anonymous research group. Laboratory experiments have been conducted in a closed office room environment.

Participants have been instructed to stand in the line of sight of ROBIN, the humanoid robot of TU Kaiserslautern, as shown in Figure 2. Three cameras are placed at different locations to record the interaction. ROBIN perception GUI is also recorded for the duration of the interaction. Artificial lights are used during the experiments to make it consistent for all the participants. An experimenter is also present in the room to monitor the processes systematically taking place and only intervene if the system malfunctions because of technical issues.

4.2 Experimental Scenarios

In the direction of validating the proposed hypothesis, participants are assessed for personality traits in three different scenarios. These scenarios have been developed with regard to a student's area of exposure that consequently leads to three relatable tasks for experimentation. Each participant has been instructed to enact the following scenarios one at a time. The experimenter also introduces participants with ROBIN at the beginning of the experiments to get familiarized with ROBIN.

The first scenario involves an interaction between ROBIN, role-playing as the professor, and the participant, role-playing as a researcher. The second scenario involves an interaction between ROBIN, role-playing as a master student, and the participant, role-playing as a supervisor. The last scenario involves an interaction between ROBIN, role-playing as an interviewer, and the participant, role-playing as a candidate. For each scenario, the robot takes the lead by asking questions and responding generically.

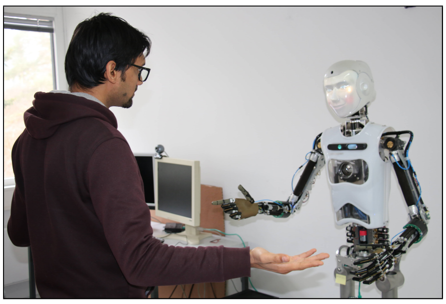

Figure 2: Humanoid robot ROBIN.

5 PERFORMANCE ANALYSIS

In order to evaluate the personality assessment system, summative evaluations are used from 5 psychology students. All the interactions are video recorded, and these videos are used for further analysis. After the experimentation, each evaluator is presented with a list of 12 personality traits and their corresponding description as follows:

1. Intellect: A person who engages in critical thinking, research, and reflection about society, proposes solutions for its problems
2. Achievement: Something done with effort & skill.
3. Extroversion: Extroverts are behaviorally more dominant in face-to-face interactions with others.
4. Social Desirability: To answer questions in a manner that is viewed to be favorable by others.
5. Arousal Seeking: A person that looks for excitement, change, new environments, take risks, etc.
6. Aggression: Readiness to attack or confront
7. Dominance: Showing power and influence
8. Physically Active: A person that is continuously active, working, organizing activities, etc.
9. Anxiety: Feeling of worry, nervousness, or uneasiness about something with uncertain outcome.
10. Shyness: Nervous or timid in company of others.
11. Sensitivity to Rejection: People who are affected easily by the negative remarks of others.
12. Nurturance: Emotional/physical care given to someone.

Observer evaluations have been used to assess human personality traits. Evaluators assess the personality traits of all the subjects using the recorded videos and descriptions of personality traits to establish the ground truth. They use the provided descriptions and their prior knowledge of human behavior to form an informed judgment about the presence (active) or absence (inactive) of each personality trait. In order to combine the outcomes from each evaluator to generate ground truth, the maximum occurrence of the outcome is used as the final outcome. For example, if two evaluators report the subject's anxiety trait as active and three evaluators report it as inactive, then the ground truth for anxiety trait of the subject is described as inactive. These assessments are compared with the system results. However, the proposed system reports the trait values between -1 to $+1$ range. For evaluation and validation, the trait with positive value is considered as active, and the trait with a negative value as inactive. Table 1 shows the recognition rates of each personality trait.

Table 1: Personality Traits and Recognition Rates.

ID	Trait Dimension	Accuracy (%)
1	Intellect	83.11
2	Achievement	78.22
3	Extroversion	91.11
4	Social Desirability	80.44
5	Arousal Seeking	87.55
6	Aggression	84.88
7	Trait Dominance	89.77
8	Physically Active	92.88
9	Anxiety	90.66
10	Shyness	78.66
11	Sensitivity to Rejection	73.33
12	Nurturance	77.77
	Average	**84.03**

5.1 Discussion

It can be seen from Table 1 that extroversion, arousal seeking, trait dominance, physically active, and anxiety traits have higher recognition rates. It is because these traits are distinct and easily distinguishable visually. For example, the system detects the presence or absence of an extroversion trait with 90% accuracy. Most of the subjects that are identified as high on extroversion trait are expressive and physically active with an open body stance during interactions, which in turn yields higher scores on the P.A.D. scale. Therefore, the system estimates the extroversion trait as active for these subjects. On the other side, some of the subjects appear to be nervous and shy during interactions, which results in lower values for the P.A.D. scale. Therefore, the system estimates the extroversion trait as inactive for these subjects. Similarly, some subjects show anxiety during interactions by exhibiting dejected and self-touching postures. Subjects are also found to be passive and restless (leaning side to side) during interactions. It has been found after analysis that dominance scores for such subjects have been negative. However, their arousal score is positive due to their movement attributed to restlessness. Therefore, the system estimates the anxiety trait as active for these subjects.

The reason for the wrong assessment of some personality traits lies in the inaccurate recognition of facial expressions. The facial expression recognition (FER) system works accurately when a person is expressing the emotions clearly. During the interaction, the facial expressions of a subject are sometimes wrongly interpreted, which affects the pleasure value. Nurturance and social desirability strongly correlate with pleasure scale as can be seen from equation 2, but due to the technical limitation of the FER system, these traits achieve low accuracy as depicted in table 1.

Due to the subjective nature of the task, evaluators themselves find it difficult sometimes to have a mutual consensus on these traits. Because of the availability of additional information such as verbal, situational, and contextual cues, evaluators labeled the ground truths of personality traits for each subject accordingly. However, the personality traits system uses only visual information to analyze human behavior and, therefore, sometimes wrongly reports a subject on a particular trait. For example, sensitivity to rejection trait is highly subjective and needs a context as well to recognize it accurately. Some subjects that exhibit submissive body postures, such as crossed arms and thinking postures, and avoid eye contact during interactions are detected as high on sensitivity to rejection trait, which may not be accurate in every case. For example, introverts also show similar body postures and head gestures, however, they may not be sensitive to rejection.

Since contextual and situational cues are not considered in this work, the system is not able to differentiate between fake personality and genuine personality. The system assesses personality based on nonverbal cues, which can also be sometimes expressed artificially. Although the subjects are instructed to enact genuinely, some may have faked their responses. Therefore, the personality assessed by the system may differ from the actual personality of the subject, which shows the importance of contextual and situational cues. However, the highly engaging nature of scenarios, along with the robot's human-like gestures and expressions, challenge the subjects to respond with minimal artificiality in this work. Hence, the system can assess different personality traits with 84% accuracy.

6 CONCLUSION

This paper proposes to use the temperament framework to describe and measure individual differences on different personality scales using P.A.D. emotional space. The proposed study has been conducted in psychology but has never been realized in HRI. In order to validate the research hypothesis, P.A.D. emotional space has been developed using the recognition / detection of nonverbal cues, such as human postures, facial expressions, proximity, activity, head gestures, etc. Using the trait equations provided in the literature (Mehrabian, 1996), a score has been calculated for each trait. For evaluation, three scenarios have been developed, and 15 university students have been invited. Due to the unavailability of the labeled data, five psychology students have been consulted to evaluate the personality traits. From validation studies, it is clear that the framework presented by Mehrabian is also applicable in HRI by using nonverbal cues.

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