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RESEARCH ARTICLE

A Comprehensive Multimodal Humanoid System for Personality Assessment Based on the Big Five Model

ANUM JAFFAR [1,2], SARA ALI [1,2,3], KHAWAJA FAHAD IQBAL [1,3], YASAR AYAZ [1,3], (Senior Member, IEEE), ALI R. ANSARI [4], MUHAMMAD A. B. FAYYAZ [5], AND RAHEEL NAWAZ [6]

[1]School of Mechanical and Manufacturing Engineering (SMME), National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan
[2]NUST-COVENTRY Human-Robot Interaction (NC-HRI) Laboratory, School of Mechanical and Manufacturing Engineering, National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan
[3]Intelligent Field Robotics Laboratory (IFRL), National Center for Artificial Intelligence (NCAI), National University of Sciences and Technology (NUST), Islamabad 44000, Pakistan
[4]Department of Mathematics and Natural Sciences, Gulf University for Science and Technology, Hawally 32093, Kuwait
[5]OTEHM, Manchester Metropolitan University, M15 6BH Manchester, U.K.
[6]Department of Digital Transformation, Staffordshire University, Staffordshire, ST4 2DE Stoke-on-Trent, U.K.

Corresponding author: Muhammad A. B. Fayyaz (m.fayyaz@mmu.ac.uk)

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ABSTRACT Personality analysis allows the experts to get insights into an individual's conduct, vulnerabilities, and prospective capabilities. Some common methods employed for personality prediction include text analysis, social media data, facial expressions, and emotional speech extraction. Recently, some studies have utilized the big five model to predict personality traits using non-verbal cues (gaze score, body motion, head motion). However, these studies mostly target only three aspects of the big five mode. None of the studies so far have used non-verbal cues to target all five traits (extraversion, openness, neuroticism, agreeableness, and conscientiousness) of the Big Five model. In this paper, we propose a multi-modal system that predicts all five personality traits of the Big Five model using non-verbal cues (facial expressions, head poses, body poses), 44-item Big Five Inventory (BFI) questionnaire, and expert analysis. The facial expression module utilizes the Face Emotion Recognition Plus (FER+) dataset trained with Convolution Neural Network (CNN) model achieving 95.14% accuracy. Evaluating 16 subjects in verbal interaction with humanoid robot NAO, we combined questionnaire feedback, human-robot interaction data, and expert perspectives to deduce their Big Five traits. Findings reveal 100% accuracy in personality prediction via expert insights and the system, and 75% for the questionnaire-based approach.

INDEX TERMS Big-five model, human-robot interaction, non-verbal cues, personality prediction, personality traits.

I. INTRODUCTION

Science fiction has led us to imagine a future in which robots assist us in daily life [1]. Researchers employ humanoid or social robots within Human-Robot Interactions, leveraging their capabilities for both interaction and personality prediction purposes by evading the uncanny valley notion [2], [3]. Since these humanoid robots were created with human characteristics, they should be able to mimic human behavior. As a result, in the realm of Human-Robot Interaction (HRI),

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the resemblance to human-human interaction is striking, with social or humanoid robots exhibiting the ability to recognize and emulate human-like characteristics [4]. A multitude of studies utilizes non-verbal indicators, encompassing kinesics, such as facial expressions, posture, gestures, and physical actions, to gain a comprehensive understanding of human behavior [5]. Thus, integrated verbal and non-verbal behaviors [6] were developed and implemented in a broad range of humanoid robots, including Pepper, NAO, ASIMO, and many more, to increase user engagement in human-robot interaction. For example, the Honda ASIMO robot can do arm and hand movements [7]. According to [8], social robots must not only behave or seem like humans, but they should also be capable of interacting with people to predict their personality attributes with integrated verbal and non-verbal behavior. This study takes a step towards this goal by evaluating personality traits accurately and reliably using a humanoid robot, personality theory, proper nonverbal cues, and a questionnaire.

To access social and personality psychology, researchers commonly employ four methods that include direct observation, informant reporting, self-reporting, and analysis of non-verbal cues [9]. Self-reporting through questionnaires may introduce biases and inaccuracies [10]. Thus, it is essential for researchers studying social behavior and personality to incorporate behavior evaluation [11]. However, quantifying behaviors alone is insufficient as they must be translated using social and personality theories.

Psychologists used Myers-Briggs Type Indicator (MBTI) [12], Cattell's 16 Factor personality [12], Eysenck's three Dimensions of personality [12], Allport's Trait theory [12], and Big Five model [13] personality prediction theories with questionnaires NEO-Five Factor Inventory (NEO-FFI) 60-item version ()() [14], International Personality Item Pool Big-Five Marker Scales (IPIP 50) [15], and 44-item Big Five Inventory (BFI) [16] for personality prediction. As time progressed the Big Five model [17] became frequently used model for personality prediction with surveys NEO-FFI, IPIP, and BFI, all of which are linked to the Big-Five model [16]. Researchers have carried out personality prediction using Big five model based on hand writing [18], through cv analysis [19], and social media text analysis [20]. Researchers have used speech [21] and non-verbal cues like eye tracking [22], emotions [23] for personality prediction using the Big Five model. Alongside social science research, studies on human-robot interaction also emphasize the significance of the Big Five model personality traits for personality prediction [24]. Researchers have synergistically combined non-verbal features to estimate personality through the utilization of robots [25]. In [26], Salam et al. focus on examining the relationship between the NAO robot and personality in both human-human interaction and human-robot interaction. It highlights the importance of considering non-verbal cues alongside verbal interaction. Non-verbal cues were extracted using an external camera. A Robin robot is used in the study [27] to identify personality traits based on body language, head movement, and emotional states. However, it concentrates only three traits (extroversion, agreeableness, neuroticism) of the Big Five model. Similarly, the detection of personality traits using the Pepper robot involves the fusion of visual and vocal features [25]. It is limited to a few features as they primarily focused on head and body motion cues alongside verbal interaction, paying attention to the impact of parameters like voice pitch, frequency, and amplitude, disregarding facial expressions. The questionnaire employed in this study was the International Personality Item Pool. In all of these studies, an expert was required from the initial stage for labeling features using personality traits.

A. CONTRIBUTION

In this study, we propose a computational framework for detecting the user's personality traits based on important visual cues (facial expressions, head pose, and body pose). The robot continues to ask the participant questions from the 44-item Big Five Inventory (BFI) questionnaire. Participants are expected to respond to the robot's questions with answers as well as their usual behavior. In the end, the robot extracts non-verbal cues and provides a prediction. Feature selection and labeling is done using the psychology literature. The following are the research contributions and novelties in this study:

1. The proposed approach combines all five Big Five personality traits (extraversion, openness, neuroticism, agreeableness, and conscientiousness), as well as verbal interaction and all nonverbal cues (facial expression (happy, sad, angry, fear, surprise), head pose (looking forward, looking up, looking down, looking left, looking right), and body pose (standing, akimbo, thinking, open arms, close arms) to predict personality.
2. A comprehensive architecture is developed to predict personalities using data from human-robot interaction (verbal and non-verbal interaction), 44-item Big Five Inventory (BFI) questionnaire, and expert opinion.
3. Within the proposed architecture, the traits of the Big Five model are linked to the feature sequences, addressing the lack of clarity in defining the correlation between traits and labeling of feature sequences, thereby enhancing the accuracy of personality prediction.
4. Using the proposed model training approach, we managed to achieve 95.14 % accuracy on the FER+ dataset, as compared to the recent research reported with an accuracy of 92.02% [28].

The remaining content of the paper is structured as follows. Section II discusses the structure of the system design and the significance of each module. The methodology is described in Section III. It provides insights on participants, experimental setup and design. Sections IV and V contain the results and discussion respectively. Finally, in Section VI, the conclusion has been presented.

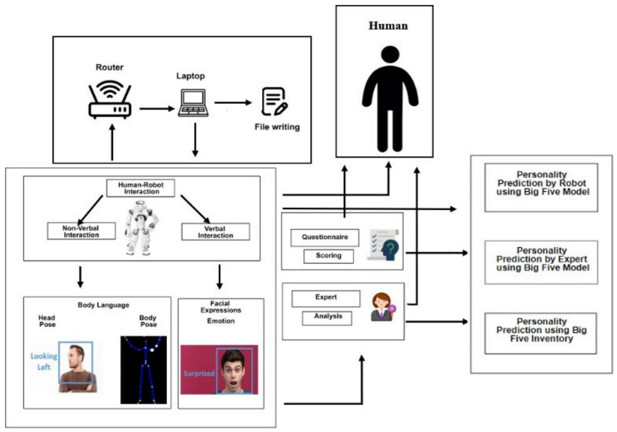


FIGURE 1. Architecture of the proposed system.

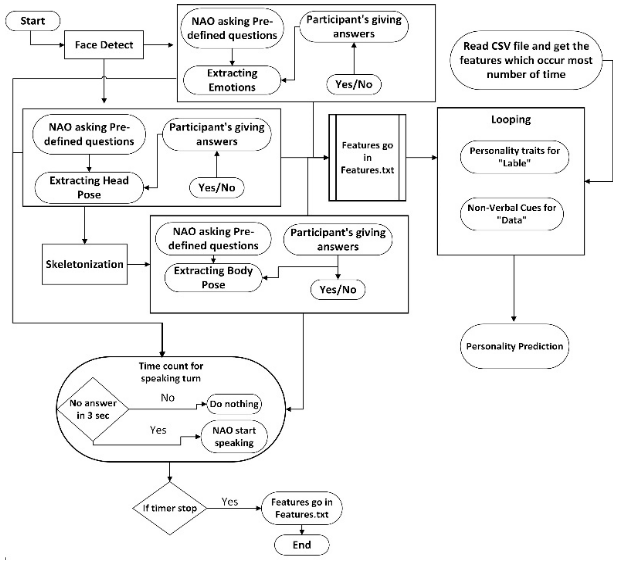


FIGURE 2. System flowchart for complete architecture explaining personality prediction based on Human-Robot Interaction (HRI).

II. ARCHITECTURE

The proposed system for personality prediction is based on the Big-Five personality model comprising of five traits i.e., extraversion, neuroticism, agreeableness, openness, and Conscientiousness [29]. These personality traits are assessed utilizing nonverbal cues such as facial expressions (happy, sad, angry, fear, surprise), head poses (looking forward, looking left, looking right, looking up, looking down) and body poses (standing, akimbo, close arms, open arms, thinking). Five key cues that are closely related to personality prediction are considered for each module after consulting with the psychologist. The architecture for the proposed research is shown in Figure 1.

The architecture utilizes verbal interaction using the BFI questionnaire for extracting non-verbal features, Big Five Inventory (BFI) questionnaire [30], [31] and expert analysis for personality prediction. Figure 2 shows the system flow chart that explains sub-modules including face detection, emotion detection, head pose estimation, skeletonization for pose estimation, data storage, and personality prediction. Table 1 shows modules along with their descriptions.

TABLE 1. Human-robot interaction modules for personality prediction.

	Human-Robot Interaction
Verbal Interaction	
Module 1	Binary Response based Interaction
Non-Verbal Interaction	
Module 2	Representation of Facial Expression
Module 3	Representation of Head Pose
Module 4	Representation of Body Pose

A. VERBAL INTERACTION: MODULE 1 (BINARY RESPONSE-BASED INTERACTION)

This system utilizes proximate human-robot interaction and incorporates a voice recognition library and utilizes the NAO robot's text-to-speech API. The robot is presented with a predetermined Big Five Inventory (BFI) questionnaire, while a speech recognition library allows access to sound recognition via a laptop or wireless microphone. Participants are instructed to respond to each question with a ''yes'' or ''no'' answer. In the absence of a response within 3 seconds, the robot proceeds to the next question. By minimizing noise and implementing necessary precautions, positive outcomes were achieved. Verbal interaction was only employed to capture the participant's attention. The primary goal was to extract nonverbal cues during the interaction.

B. NON-VERBAL INTERACTION: MODULE 2 (FACIAL EXPRESSION)

The growing need for automated emotion recognition systems has led to significant research in the field of human-computer interactions [32]. Emotion recognition can be achieved through various modalities such as speech, text, facial cues, and EEG-based brain waves [33]. Emotion recognition can be done by two methods. The first technique is unimodal, while the second is multimodal. Unimodal approaches evaluate emotions using a single modality e.g., speech, EEG, facial expressions, while multimodal approaches combine multiple modalities for emotion estimation [34].

Wearable technologies [35] and libraries [36] are being used in recent studies to identify emotions. We aimed to assess if new libraries hinder or blend well with robot systems. So, we chose practical options that fit our algorithm's diverse modes. Regarding wearable technology it has the potential to raise the consciousness of respondents in personality research. People's actions and outcomes might change when they are aware they are being observed; this is known as the Hawthorne effect [37]. Hence, instead of employing physiological factors [38] from wearable technologies this research focuses on employing a unimodal technique that utilizes physical signals represented by facial expression [38]

TABLE 2. Model training formulas for emotion recognition using robot.

Operations	Formulas
Convolutional layer	$C^1 = P^{1-1} * w^1$
Max Pooling	$P^1_{xy} = max\, P^{1-1}(x + \mathrm{i})(y + j)$
Fully Connected Layer	$C_l = w_l * P_{l-1}$
ReLU	$Re\,Lu_{(c_J)} = max(0, C_j)$
Softmax	$Soft\,max(C_i) = e^{c_i} / \Sigma_j e^c j$

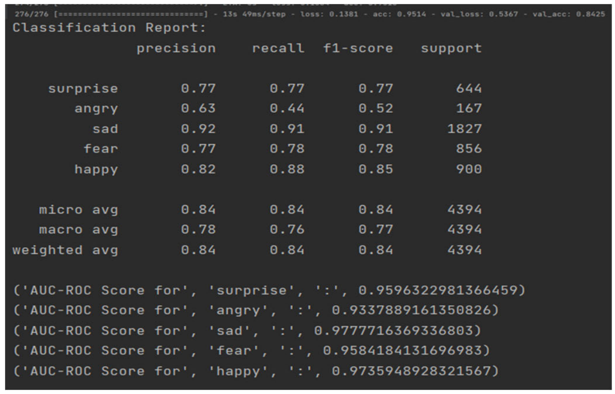
for five universal emotions: Happy, Sad, Fear, Angry, and Surprised [39] measured by robot.

Recent studies frequently employ Convolutional Neural Networks (CNNs) in conjunction with the FER 2013 and FER+ datasets. Reported accuracies on the FER 2013 dataset include 71.61% [40], 74.23% [41], 82.1% [42], 74.50% [43], 69.49% [44], 89% [45], and 94.5% [46]. Accuracies achieved on the FER+ dataset are 92.02% [28], 89.50% [41], 84.633% [44], and 86.58% [47]. Notably, these studies have not explored the use of emotion recognition for personality prediction. In contrast, our research utilizes CNNs with the FER+ dataset [48], an enhanced version of FER 2013, concentrating on five specific emotions within the facial module, which constitutes one of the four modules employed for personality prediction. Using the proposed model training approach, we managed to achieve 95.14 % accuracy on the FER+ dataset shown in Figure 3, as compared to the recent research reported with an accuracy of 92.02% [28].

For emotion recognition, feature extraction and classification are crucial. A four-layer convolutional architecture with two fully connected convolutional layers was selected for training a CNN model using Keras and CNTK at backend. The fully connected layers aid in picture classification, while the convolutional layers extract essential image characteristics. The ReLU function handles CNN's non-linearity, followed by pooling to reduce dimensionality. Each layer incorporates batch normalization and dropout methods. Activation is achieved using the softmax function. Table 2 shows the mathematical model for training CNN.

The classification report is presented in Figure 3. The majority of the classes have strong precision, recall, and F1 scores. Moreover, the model demonstrates proficiency in distinguishing between emotional instances and non-emotional ones, as indicated by robust AUC-ROC scores.

Figure 4 depicts the emotion classification model's performance using a normalized confusion matrix. The ground truth/real emotions in the data samples are represented by rows and the model's anticipated emotions are represented by columns. The confusion matrix shows the percentage of data points from a given class that were assumed to belong to a different class. For instance, 1% of the surprise data samples were incorrectly identified as angry, whereas 77% of the samples were correctly classified. Overall, in the proposed model training approach, we managed to achieve 95.14 % accuracy, correctly recognizing the majority of the data points.


```
276/276 [==============================] - 13s 49ms/step - loss: 0.1381 - acc: 0.9514 - val_loss: 0.5367 - val_acc: 0.8425
Classification Report:
              precision    recall  f1-score   support

    surprise       0.77      0.77      0.77       644
       angry       0.63      0.44      0.52       167
         sad       0.92      0.91      0.91      1827
        fear       0.77      0.78      0.78       856
       happy       0.82      0.88      0.85       900

   micro avg       0.84      0.84      0.84      4394
   macro avg       0.78      0.76      0.77      4394
weighted avg       0.84      0.84      0.84      4394

('AUC-ROC Score for', 'surprise', ':', 0.9596322981366459)
('AUC-ROC Score for', 'angry', ':', 0.9337889161350826)
('AUC-ROC Score for', 'sad', ':', 0.9777716369336803)
('AUC-ROC Score for', 'fear', ':', 0.9584184131696983)
('AUC-ROC Score for', 'happy', ':', 0.9735948928321567)
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FIGURE 3. Classification report representing precision, recall, f1-score, and support along with AUC-ROC score.

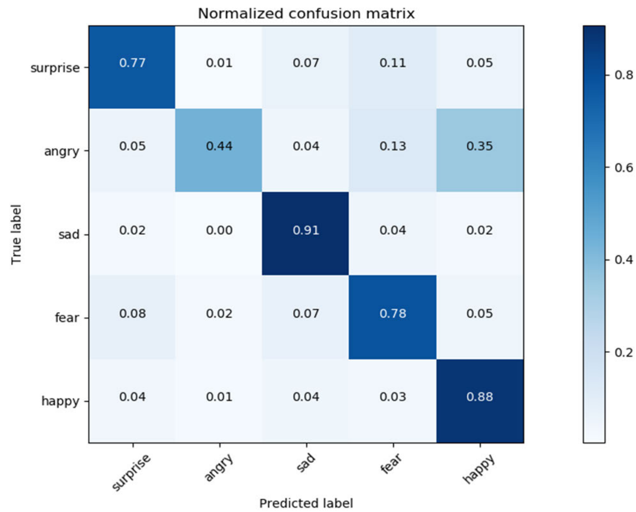

FIGURE 4. Confusion matrix.

Figure 5 shows ROC curves that plot the TPR (True Positive Rate) on the y-axis and the FPR (False Positive Rate) on the x-axis for five emotions i.e., surprise, anger, sorrow, fear, and happiness. The area under the curve (AUC) is also presented for each class, indicating the likelihood that the model will rate a positive instance higher than a negative one. The model had the greatest AUC for sadness (0.98), followed by surprise (0.96), fear (0.96), happiness (0.97), and anger (0.93). These findings show that the model performed well in identifying all five emotions, with sadness showing the greatest performance.

After training the model, the person face was detected using the Haar Cascade frontal face detection model, which employs edge and line detection techniques proposed by [49]. Live NAO robot camera captured frame-by-frame input by displaying emotion labels. Table 3 shows the model testing results. An individual's facial expressions during engagement or communication are more significant. Traits correlated with emotions are as follows: Most individuals smile during conversations, while fear or sadness is exhibited when they are uncertain about communication. Rage is displayed when a person is upset, and surprise is shown in response to shocking

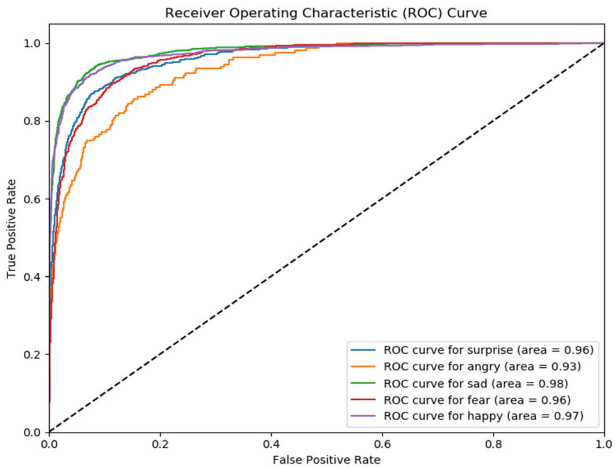

FIGURE 5. AUC-ROC curves.

TABLE 3. Result of emotion recognition.

Testing	Human Input	Prediction
1	happy	happy
2	angry	angry
3	sad	sad
4	angry	angry
5	surprise	fear
6	fear	fear
7	happy	happy
8	surprise	surprise
9	fear	surprise
10	surprise	surprise

TABLE 4. Big-five model correlation with emotions.

	Big-Five Model Features				
Traits	Happy	Sad	Fear	Angry	Surprise
Extraversion	+	-	-	-	+
Agreeableness	+	0	+	-	0
Neuroticism	+	+	+	+	0
Openness	+	+	-	-	-
Conscientiousness	+	-	-	-	-

events. Table 4 shows the correlation of facial emotions with traits of the Big Five model [50].

C. NON-VERBAL INTERACTION: MODULE 3 (HEAD POSE)

Face appearances are influenced by head position, which also indicates the intended interaction of the user. Psychology research has demonstrated that gaze prediction is influenced by both head posture and eye direction [51]. Head pose estimation in computer vision refers to determining the orientation of an object relative to the camera. In this research, five main head positions (looking ahead, up, down, left, and right) are employed.

The Geometric Method is employed for head position estimation, utilizing facial landmarks and projective geometry. The human head has three degrees of freedom (DOF) in relation to the camera: roll, pitch, and yaw [52]. The first step involves establishing a reference frame. Subsequently, the perspective-n-point problem (PnP) was employed to calculate the head's pose (location and orientation) with respect to the camera. Equation 1 was utilized in this instance.

$$s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & \gamma & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \tag{1}$$

Once the pose of the head is determined using PnP, Euler angles were used to depict the head's orientation in 3D space. Euler angles are an intuitive and easily understandable way to represent head orientation, which is often split into rotations around the three major axes (roll, pitch, and yaw). This is represented in Equation 2 for finding out which way the head is facing. X, Y, and Z denote the original coordinates of a point or vector in three-dimensional space. The angles ψ (psi), θ (theta), and φ (phi) indicate the degree of rotation along the x, y, and z axes correspondingly. By multiplying these matrices in the specified sequence, we sequentially apply the rotations. The resultant combined rotation matrix depicts the overall rotation applied to either a point or a rigid body.

$$\begin{aligned} &R_x(\psi)\,R_y(\theta)\,R_z(\phi)\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \\ &= \begin{bmatrix} cos\psi & -sin\psi & 0 \\ sin\psi & cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} cos\theta & 0 & sin\theta \\ 0 & 1 & 0 \\ -sin\theta & 0 & cos\theta \end{bmatrix} \\ &\quad \times \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\phi & -sin\phi \\ 0 & sin\phi & cos\phi \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \end{aligned} \tag{2}$$

Previous studies utilized six face landmarks [53] for head posture estimation. Following that, the dlib library was utilized to detect faces and landmarks. While our study employed eight landmarks (two points for the nose, two points for the eyes, one point for the chin, and three points for the mouth). The dlib library allowed the recognition of 68 landmarks [54]. Hence, a pre-trained frontal face detector from dlib was used for face recognition. Camera posture was calculated and represented as vectors, from which Euler angles were derived. Previous study has utilized, head yaw ranges from −15 to +15 degrees, and head pitch ranges from −30 to +30 degrees [55]. Using this in our study poses are distinguished. Frame-by-frame input was captured from the Nao robot live camera with displaying head pose labels. Testing results are present in Table 5.

The most frequently used head pose is facing forward, whereas facing right is the least used. When individuals want to connect or communicate, they look at the other person.

TABLE 5. Result of head pose estimation.

Testing	Human Input	HPE Analyzer
1	Looking Forward	Looking Down
2	Looking Left	Looking Left
3	Looking Right	Looking Right
4	Looking Up	Looking Up
5	Looking down	Looking Forward
6	Looking Forward	Looking Forward
7	Looking Left	Looking Left
8	Looking Right	Looking Right
9	Looking Up	Looking Up
10	Looking down	Looking Down

TABLE 6. Big-five model correlation with head pose.

	Big-Five Model Features				
Traits	Looking Forward	Looking Up	Looking Down	Looking Left	Looking Right
Extraversion	+	+	-	-	0
Agreeableness	+	-	+	-	0
Neuroticism	-	-	+	+	-
Openness	+	-	-	-	-
Conscientiousness	+	-	-	-	-

Conversely, when they want to avoid or refrain from communicating, they occasionally look down, to the right, to the left, and up. The connection of traits with head posture is present in Table 6 [56].

D. NON-VERBAL INTERACTION: MODULE 4 (BODY POSE)

The endeavor of anticipating the positions of the human body's joints is referred to as human body pose estimation. 2D posture estimate is the process of determining the x, y coordinates for each joint [57]. Basic poses: standing, open arms, closed arms, akimbo, and thinking are selected. Skeletonization was done using MPII model [58]. For each key point, a confidence map was generated, and a blob appeared on each joint in the live camera feed. These blobs were connected to create a skeleton frame using lines. The second step involved calculating the distance between joints and using the law of cosine [59] to determine joint angles. Mathematical models for calculating distance and joint angle are shown below.

$$Dis = \sqrt{(b-a)^2 + (d-C)^2} \tag{3}$$

$$\theta = \arccos\left(\frac{ab \cdot cb}{|ab| \cdot |cb|}\right) \tag{4}$$

Initially, each pose is described in terms of joint angles; for example, standing usually consists of straight legs with arms hanging naturally by the sides. Shoulders, elbows, and wrists are among the relevant joints that are crucial for characterizing each position. Joint angles data from 20 subjects with heights ranging from 5'1'' to 6'3'' was collected and stored in the csv file. Understanding the distinctive joint angles connected to each pose is necessary in order to set angle thresholds for identifying particular body postures. To determine the normal ranges of movement for each relevant joint in the intended position, joint angle ranges were analyzed.

TABLE 7. Result of body pose estimation.

Testing	Human Input	BPE Analyzer
1	Close arms	Open arms
2	Standing	Standing
3	Open arms	Close arms
4	Thinking	Thinking
5	Akimbo	Akimbo
6	Close arms	Close arms
7	Open arms	Open arms
8	Standing	Standing
9	Akimbo	Akimbo
10	Thinking	Thinking

TABLE 8. Big-five model correlation with body pose.

	Big-Five Model Features				
Traits	Standing	Close arms	Open arms	Thinking	Akimbo
Extraversion	+	-	+	-	+
Agreeableness	-	+	-	+	-
Neuroticism	-	+	-	+	+
Openness	+	-	+	+	+
Conscientiousness	+	-	+	-	-

These ranges are then used to establish angle thresholds that differentiate between the poses. Testing was done to iteratively refine these thresholds. Elements such as body proportions, clothes, lighting circumstances, and potential obstacles are also taken into account to ensure that the thresholds are resilient across varied settings. Frame-by-frame input was captured using the Nao robot live camera, which displayed body pose labels. Table 7 shows the testing results.

Table 8 shows the link between the Big Five model traits and the body postures [27], [60], [61], [62]. Typically, an upright standing position or open arms indicates the intention to communicate, while a close-arm stance suggests a lack of interest in communication. The pose of one hand on the chin and the other arm closed signifies a thinking posture. The akimbo pose is considered a power pose [62], which can be used to display dominance or it can be adopted casually.

E. FEATURE LABELLING & TRAITS CORRELATION

The feature sequences were made based on previous literature related to the traits of the Big Five model [27]. These sequences were also verified by a psychologist/expert. The number of possible sequences for each trait was determined based on positive correlation of features with each trait. Table 9 shows the features sequence correlation with traits. A positive correlation indicates a positive association with a trait, a negative correlation indicates a negative association, and zero represents no correlation. In this study negative correlation features are not used because it is related to the reverse of each trait. The correlation between specific traits can also be observed within sequences of features, and

TABLE 9. Features sequences correlation with traits.

Traits	Human Features		
	Emotion	Head orientation	Body Pose
Extraversion	Happy	Looking Forward	Open arms
	Happy	Looking Forward	Standing
	Happy	Looking Forward	Akimbo
	Happy	Looking Up	Open arms
	Happy	Looking Up	Standing
	Happy	Looking Up	Akimbo
	Surprised	Looking Forward	Open arms
	Surprised	Looking Forward	Standing
	Surprised	Looking Forward	Akimbo
	Surprised	Looking Up	Open arms
	Surprised	Looking Up	Standing
	Surprised	Looking Up	Akimbo
Agreeableness	Happy	Looking Forward	Close Arms
	Happy	Looking Forward	Thinking
	Happy	Looking Down	Close Arms
	Happy	Looking Down	Thinking
	Fear	Looking Forward	Close Arms
	Fear	Looking Forward	Thinking
	Fear	Looking Down	Close Arms
	Fear	Looking Down	Thinking
Neuroticism	Sad	Looking Left	Close Arms
	Sad	Looking Left	Akimbo
	Sad	Looking Left	Thinking
	Sad	Looking Down	Close Arms
	Sad	Looking Down	Akimbo
	Sad	Looking Down	Thinking
	Angry	Looking Left	Close Arms
	Angry	Looking Left	Akimbo
	Angry	Looking Left	Thinking
	Angry	Looking Down	Close Arms
	Angry	Looking Down	Akimbo
	Angry	Looking Down	Thinking
	Fear	Looking Left	Close Arms
	Fear	Looking Left	Akimbo
	Fear	Looking Left	Thinking
	Fear	Looking Down	Close Arms
	Fear	Looking Down	Akimbo
	Fear	Looking Down	Thinking
	Happy	Looking Left	Close Arms
	Happy	Looking Left	Akimbo
	Happy	Looking Left	Thinking
	Happy	Looking Down	Close Arms
	Happy	Looking Down	Akimbo
	Happy	Looking Down	Thinking
Openness	Happy	Looking Forward	Open Arms
	Happy	Looking Forward	Standing
	Happy	Looking Forward	Akimbo
	Happy	Looking Forward	Thinking
	Sad	Looking Forward	Open Arms
	Sad	Looking Forward	Standing
	Sad	Looking Forward	Akimbo
	Sad	Looking Forward	Thinking
Conscientiousness	Happy	Looking Forward	Open Arms
	Happy	Looking Forward	Standing

TABLE 10. Correlation between traits.

Traits	Correlation	Traits
Extraversion	Positive Weak Correlation	Openness
Extraversion	Positive Weak Correlation	Conscientiousness
Agreeableness	Moderate Negative Correlation	Neuroticism
Openness	Positive Weak Correlation	Conscientiousness
Conscientiousness	Positive Weak Correlation	Openness
Agreeableness	Positive Noticeable Correlation	Openness

previous psychology research has demonstrated the existence of correlations among these traits. Table 10 shows the correlation between traits.

F. PERSONALITY PREDICTION: QUESTIONNAIRE & EXPERT ANALYSIS

This research utilizes the 44-item BFI (Big Five Inventory) questionnaire [30], [31] to assess participant's personality based on the big five model traits. Participants were asked to fill in the questionnaire and their personalities were identified based on the responses. The participant's personality was also revealed by an expert after analyzing the human-robot interaction and data that was taken during the interaction of 16 participants.

III. MATERIALS & METHODS

This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at NC-HRI. Informed consent was obtained from each participant.

A. SUBJECTS

The personality prediction system was evaluated on the data of 16 participants, comprising both males and females, who were recruited from the university. Before participation, the participants signed a consent form to allow for the collection and analysis of their data by psychologist.

B. ENVIRONMENTAL SETUP

The NAO robot was placed on the table in a relaxed sitting position in front of the participant. While participant was standing at the distance of 5.7 feet from the table so the NAO robot upper camera can see full body of the participant.

FIGURE 6. Labelling of different modules using NAO camera during a human-robot interaction.

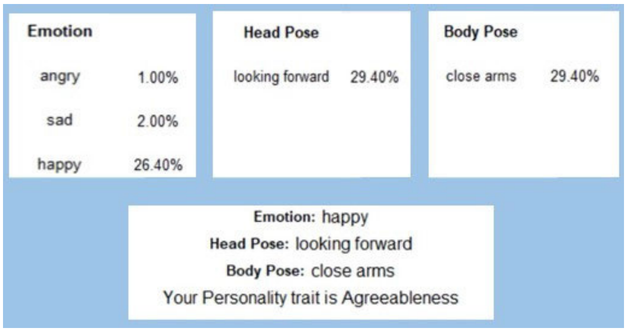

FIGURE 7. Graphical User Interface (GUI) for personality prediction using human-robot interaction.

C. EXPERIMENTAL DESIGN

The robot and laptop were connected via a router and an Ethernet wire. Following the SOLER [63] acronym: S for Squarely meaning opt positive stance, O for open posture, L for leaning, E for eye contact, and R for relaxed, the robot was positioned at the table. Psychologists and counselors follow this acronym in interaction with a person. During the interaction, the participant was standing 5.7 feet away and had the choice of using a laptop microphone or a wireless microphone. Features were extracted using the Nao robot upper camera with each module running sequentially for 40 seconds. All modules data was stored in a file. At the end data was used by robot for personality prediction.

D. DATA PROCESSING

For verbal interaction NAO robot API, "ALTextToSay" was used and for participant speech recognition laptop or wireless microphone. For measuring emotion, head pose, and body pose upper camera of NAO robot was used. The color space was BGR with 15 frames per second. All the data was stored in a readable file.

IV. RESULTS

A. PERSONALITY PROFINING SYSTEM (PPS)

During the sequential execution of the modules, the NAO robot's camera recorded real-time data, capturing labels for emotion prediction, head position estimation, and body pose estimation shown in Figure 6. The resulting labels were saved in a file. The system then presented an interface displaying the weightage of observed features during the experiment and the predicted personality based on those features. This information was presented through a graphical user interface (GUI) as shown in Figure 7. The experiments involved a total of 16 participants.

B. QUESTIONNAIRE (QU)

As In the experiment with 16 participants, each participant was asked to complete a questionnaire. The questionnaire was scored using the methodology outlined in [30] and [31]. By examining the participant's highest and lowest scores across the five personality traits, their dominant personality traits were identified. These traits were then used to generate a comprehensive personality profile for each participant.

C. EXPERT ANALYSIS (EA)

To ascertain the personality of each participant, an expert was enlisted to evaluate the participant data obtained during human-robot interaction and the recorded data from those interactions. Features were quantified based on their frequency of occurrence, as deemed the most reliable approach by experts. The features that appeared most frequently were selected for personality prediction. The expert analyzed the data of all 16 participants in the study.

V. DISCUSSIONS

The understanding of personalities through questionnaires is crucial. However, relying solely on a single questionnaire assessment to draw definitive conclusions about a person's personality may be limited, as personality is complex and multifaceted. Instead, it is important to consider a comprehensive assessment that takes into account various characteristics and aspects of an individual's personality [64], [65]. To gain a better understanding of personality, nonverbal cues were extracted during human-robot interaction, and expert input was sought to validate the accuracy of the personality predictions made by the system. While the questionnaire assessments may have included some incorrect predictions, the consistency between the participant's interactions with the robot and the expert analysis results adds confidence to the accuracy of the predictions.

According to the questionnaire, participant 5 exhibited extraversion; nonetheless, expert analysis and robot predictions revealed extraversion as having favorable associations with openness and conscientiousness. During Human-Robot Interaction (HRI) and expert analysis, participants 7 and 9, who were previously categorized as extraverted by the questionnaire, demonstrated extraversion with a positive association with openness. Following HRI and expert analysis, Participant 10, who had been initially classified as neurotic in the questionnaire, turned out to be agreeable with a weak negative correlation with neuroticism. These instances highlight the questionnaire's limited ability to identify traits based on correlations, underlining the importance of combining questionnaire results with additional approaches such as expert analysis and HRI for a more accurate understanding of personality traits. Participant 8, who was classified as

TABLE 11. Results of personality prediction.

Subjects	Questionnaire Result	Interaction Result	Expert Analysis
P1	Neuroticism	Neuroticism	Neuroticism
P2	Agreeableness	Agreeableness	Agreeableness
P3	Extraversion	Extraversion	Extraversion
P4	Extraversion	Extraversion	Extraversion
P5	Extraversion	Extraversion with a positive weak correlation with Openness & Conscientiousness	Extraversion with a positive weak correlation with Openness & Conscientiousness
P6	Neuroticism	Neuroticism	Neuroticism
P7	Extraversion	Extraversion with a positive weak correlation with Openness	Extraversion with a positive weak correlation with Openness
P8	Conscientiousness	Openness	Openness
P9	Extraversion	Extraversion with a positive weak correlation with Openness	Extraversion with a positive weak correlation with Openness
P10	Neuroticism	Agreeableness with negative moderate correlation with Neuroticism	Agreeableness with negative moderate correlation with Neuroticism
P11	Neuroticism	Neuroticism	Neuroticism
P12	Conscientiousness	Neuroticism	Neuroticism
P13	Openness	Openness	Openness
P14	Agreeableness	Agreeableness	Agreeableness
P15	Agreeableness	Agreeableness	Agreeableness
P16	Conscientiousness	Extraversion	Extraversion

conscientious in the questionnaire, indicated openness in both the interaction and the expert evaluation.

In contrast, the results of participants 12 and 16 showed variation; the conscientiousness trait emerged from the questionnaire, while in the case of HRI and expert analysis, respectively, it revealed neuroticism and extraversion. These scenarios point to possible manipulation of the questionnaire responses by the user. However, reliable and precise outcomes were achieved by combining a robot interaction system with expert analysis; this emphasizes the significance of alternative methods for a deeper evaluation of personality traits. All things analyzed, extraversion was the most frequent feature, whereas openness was the least common. Additionally, there was no conclusive connection shown for conscientiousness. Table 11 and Figure 8 show a graphical representation of these findings. Figure 9 shows a graphic representation of the percentage occurrence of each feature. Following limitation of this research can be addressed for future work:

1. The study's limitation lies in its potential to broaden the sample size to include diverse demographics and cultures, which may impact the applicability of the suggested multi-modal system.

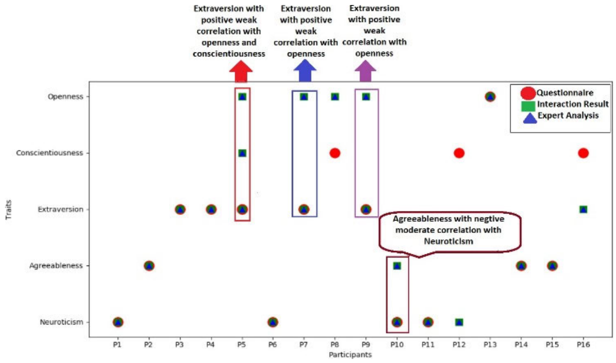

FIGURE 8. Result plots of personality profiling system, questionnaire, expert analysis.

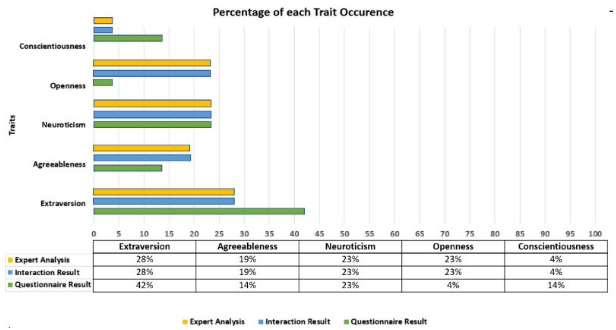

FIGURE 9. Percentage occurrence of each trait.

2. A controlled study is conducted. The presence of a humanoid robot may cause individuals to behave differently, or display altered non-verbal indicators, which could affect how accurate personality predictions are assessed.
3. During clinical sessions for personality assessment, experts employ a comprehensive methodology for assessing an individual's emotions, body language, head posture, gaze, voice tone, and the shape of their body parts. Integrating the body's form cue may improve personality prediction algorithm accuracy and resilience. Nevertheless, since clothing plays a significant role in body shape, there is a lack of data on it, making it challenging for robots to recognize human forms.

Aside from its limitations, the research holds following theoretical implications:

1. As questionnaires have inherent limits in providing complete evaluations, therefore, by including both verbal and nonverbal indicators with expert analysis, the study advances multi-modal personality prediction. Thereby bridging the gap between traditional questionnaire-based evaluations and new developments in affective computing by providing a more complete view of personality traits.
2. The study sheds light on the underlying mechanisms and relational signs of each of the Big Five personality traits by connecting particular non-verbal cues to them. This enhanced comprehension could inspire the

development of more sophisticated and precise models and tools for personality assessment.

3. Using the proposed modular emotion model training approach,, we managed to achieve 95.14 % accuracy on the FER+ dataset, as compared to the recent research reported with an accuracy of 92.02% [28].
4. This research work contributes to the scholarly discussion in the fields of personality analysis and human-robot interaction by addressing study limitations and exploring theoretical implications. It also shows critical thought on the methodology, findings, and broader implications of the study such as increasing the sample size, looking into more nonverbal indicators, improving the prediction models, and verifying the findings across a range of demographics and real-world situations.

VI. CONCLUSION

To conclude, this investigation employed an inventive technique to anticipate personality characteristics using Human-Robot Interaction (HRI), combined nonverbal cues (facial expressions and body language) along with verbal communication, a 44-item Big Five Inventory (BFI) survey, and an expert analysis to predict personality based on the Big Five model. A humanoid robot NAO was used in an interactive verbal session to gather nonverbal cues such as facial expressions, head position and body position for personality prediction. The facial expression module used the Face Emotion Recognition Plus (FER+) dataset trained with Convolutional Neural Network (CNN) for emotion recognition. The head position module determined head angles using Euler angles, while the body position was estimated by computing shoulder and elbow joint angles using the law of cosine. The experimentation involved 16 participants age ranges 21-30, for predicting personality characteristics i.e., extraversion, neuroticism, agreeableness, openness, and conscientiousness. The results of predicting personality traits in interaction between human and robot were consistent with assessment made by psychologists. These findings demonstrate the potential of using Human-Robot Interaction (HRI) in anticipating personality characteristics based on the Big Five model. The integration of multiple data sources, including survey responses, human-robot interaction, and professional analysis, provides a comprehensive approach to enhance the accuracy of personality prediction. Further research and refinement of the methodology could lead to practical applications in fields such as human-robot interaction, psychology, and personalized user experiences.

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ANUM JAFFAR received the M.S. degree in robotics and intelligent machine engineering from the Department of Robotics and Intelligent Machine Engineering, NUST-COVENTRY Human-Robot Interaction (NC-HRI) Laboratory, School of Mechanical and Manufacturing Engineering, National University of Sciences and Technology (NUST), Islamabad, Pakistan, in 2023, where she is currently pursuing the degree. Her research interests include human–robot interaction, interactive robotics, machine learning, and computer vision.

SARA ALI received the master's degree in research from the Faculty Development Program, Middlesex University London, U.K., in 2013, and the Ph.D. degree in robotics and intelligent machine engineering from the School of Mechanical and Manufacturing Engineering, National University of Sciences and Technology (NUST), Pakistan, in 2020. She is currently an Assistant Professor with the Department of Robotics and Intelligent Machine Engineering, NUST. She is the Principal Investigator (PI) of two main laboratories, the Intelligent Field Robotics Laboratory (IFRL), and the Human-Robot Interaction (HRI) Laboratory, NUST. She has published more than 40 research papers in international peer-reviewed journals and conferences, including citations from Nature. She has authored a book entitled *Introducing Therapeutic Robotics for Autism* (U.K.: Emerald Publishing Ltd.) Her research interests include human–robot interaction, sensor systems, interactive robotics, virtual reality, and human–machine interaction. She was appointed as the session chair and a member of the Scientific Advisory Board (SAB) of several prestigious international conferences. She was also awarded the National Patent on Brain Imaging Tool for Medical Diagnosis.

KHAWAJA FAHAD IQBAL received the B.E. degree in mechatronics engineering from the National University of Sciences and Technology (NUST), Islamabad, Pakistan, in 2011, and the M.S. degree in bioengineering and robotics and the Ph.D. degree in robotics from Tohoku University, Japan, in 2017 and 2022, respectively. He is currently an Assistant Professor and a Post-Graduate Program Coordinator with the Department of Robotics and Artificial Intelligence, School of Mechanical and Manufacturing Engineering (SMME), NUST. He is also the Co-Principal Investigator of the Intelligent Robotics Laboratory (IRL), National Center of Artificial Intelligence (NCAI), Pakistan. He is the Founding CEO of Rising Automation Pvt. Ltd., which is a spin-off of NUST registered with the National Science and Technology Park (NSTP). It provides consultancy and training to traditional institutes, local industries, and SMEs, and helps them automate their products and services. He received Japanese Government (MEXT) Scholarship for both the M.S. and Ph.D. degrees. He has authored more than 20 research papers in well-reputed international journals and peer-reviewed conferences. His research interests include collaborative robots, motion planning, reinforcement learning, natural language processing, augmented reality, and simultaneous localization and mapping (SLAM). He is a member of the IEEE Robotics and Automation Society and the MEXT Alumni Association of Pakistan.

YASAR AYAZ (Senior Member, IEEE) received the Ph.D. degree specializing in intelligent robotics from Tohoku University, Japan. He is currently a Professor of artificial intelligence and robotics with the National University of Sciences and Technology (NUST), Pakistan. He also heads Pakistan's National Center of Artificial Intelligence (NCAI) as the Chairperson. He also holds the title of a Specially Appointed (Associate) Professor with the Department of Bioengineering and Robotics, Graduate School of Engineering, Tohoku University. His research interests include the design, motion planning, navigation, and control of humanoids, mobile robots, and bionic systems.

ALI R. ANSARI was the Dean of the College of Arts and Sciences, Gulf University for Science and Technology, Kuwait, for ten years, where he is currently a Professor of applied mathematics. He has more than 100 publications in the area of applied mathematics. He has more than 30 years of experience in teaching and research in the area of applied mathematics.

MUHAMMAD A. B. FAYYAZ received the bachelor's degree in mechanical engineering and the Ph.D. degree from Manchester Metropolitan University (MMU), in 2017. He is currently a Lecturer of business analytics and statistics and visualization with the OTEHM Department, MMU. His Ph.D. research topic was the integration of AI into the safety aspect of the railway system in Britain. He received the Full Scholarship for the Ph.D. degree from MMU. He has strong academic/technical experience in applied AI, in particular, computer vision and data analytics. He is involved in different national and international research projects in applied AI and data analytics.

RAHEEL NAWAZ is currently the International Thought Leader in higher education and industry-academia co-design, who has advised national governments, policy organizations, parliamentary committees on AI, and digital education and work-based Learning. At Staffordshire University, he leads transformative action across the university to deliver an enhanced academic experience. With four books and more than 200 research articles, he ranks among the top ten most cited scholars in the world in the fields of applied AI, digital education, educational data science, and digital transformations. His sector-leading work on pedagogical design and delivery led to outstanding student outcomes, with first-generation university students with minimal prior attainment outperforming graduates of top U.K. universities (including Oxbridge) in both average salaries and job security. He has advised on the establishment and launch of work-based learning degree programs across three continents and received the Principal Fellowship of the Higher Education Academy (PFHEA) for this work. The impact of his academic leadership has been endorsed by heads of state, government ministers, and industry leaders. He passionately believes that kindness is the most impactful leadership trait and that being an intrinsic giver in life is the most sustainable route to happiness, as outlined in his TEDx talk. He was awarded the National Teaching Fellowship (NTF) for this work.