Human Robot Interaction- Personality Prediction of a Human Using Humanoid Robot

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Copyright Statement

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Abstract

This study presents an innovative approach to predicting personality traits by utilizing Human-Robot Interaction (HRI). The research focuses on predicting personality traits based on the Big Five model. The study incorporates nonverbal cues, such as facial expressions and body language, along with verbal interaction, a 44-item Big Five Inventory (BFI) questionnaire, and expert analysis. To facilitate the interactive session and personality prediction, a humanoid robot named NAO was employed. The robot interacted verbally with the participants, and during these interactions, it captured nonverbal cues, specifically facial expressions (happy, sad, fear, angry, and surprised), head pose (looking forward, looking up, looking down, looking left, and looking right), and body poses (standing, akimbo, close arms, open arms, and thinking). For facial expression analysis, the researchers employed the Face Emotion Recognition Plus (FER+) dataset, which was trained using Convolution Neural Network (CNN). This module enabled the recognition of different facial expressions associated with emotions. The head poses module determined head angles using Euler angles, while the body pose was estimated by calculating the shoulder and elbow joint angles using the law of cosine. The proposed system was tested on 16 participants aged between 21-30 years to access traits i.e., extraversion, neuroticism, agreeableness, openness, and conscientiousness by integrating questionnaire response, human-robot interaction, and expert analysis. Results of the study indicate a significant association between the personality predictions made by the robot and the assessments conducted by psychologists. In all 16 cases, the predicted personalities were consistent with the expert opinions. This suggests that the extensive utilization of nonverbal cues, combined with verbal interaction, holds potential for personality prediction using the Big Five model. Overall, this study demonstrates an innovative approach to personality prediction, leveraging Human-Robot Interaction and integrating multiple data sources. By incorporating nonverbal cues alongside verbal interaction and expert analysis, the proposed architecture shows promise in predicting personality traits based on the Big Five model.

Key Words: : Personality Assessment; Personality Prediction; Non-verbal cues; Big-five model, Personality trait

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CHAPTER 1

INTRODUCTION

Social networking has become an integral element of modern life. Every active user can create a post that includes text or graphics. Their personalities are reflected in their posts. This method can collect a vast amount of data that can be used to predict personality. Many studies on personality prediction using social media postings have been published. but now robots are well-known in this field and much study has already been conducted. Science fiction has led us to imagine a future in which humanoid robots assist us in the daily aspects of our lives. Humanoid or social robots come in a variety of shapes and sizes that are used in human-robot interactions. Some are common, while others are less.

Researchers utilize a lot of robots in personality prediction work. In the realm of rehabilitation, these humanoid robots are well-known, although designers are cautious to avoid the Uncanny valley idea [1], [2] and uncanny valley graph [3] can be seen in Figure 1. However, these humanoid robots are developed with human traits, it is widely assumed that humanoid robots should imitate humans. As a result, human-robot-interaction (HRI) is very similar to human-human-interaction, and the ability to recognize human-like features is the definition of a social or humanoid robot [4]. Nonverbal cues are used in many studies to understand human behaviors. Non-verbal communication that includes bodily motions, posture, gestures, and facial expressions is referred to as kinesics [5].

1.1 Problem Statement

At present there is a lot of research focus on the personality prediction using text and social media platform [6], facial expressions [7] and from emotion speech [8] but there are few studies in which robots are used for personality prediction. There is no study using all the nonverbal features: emotion, head pose, and body pose with five traits of big five model. This study focuses on predicting personalities using data from human-robot interaction, questionnaire, and expert opinion using the big five model.

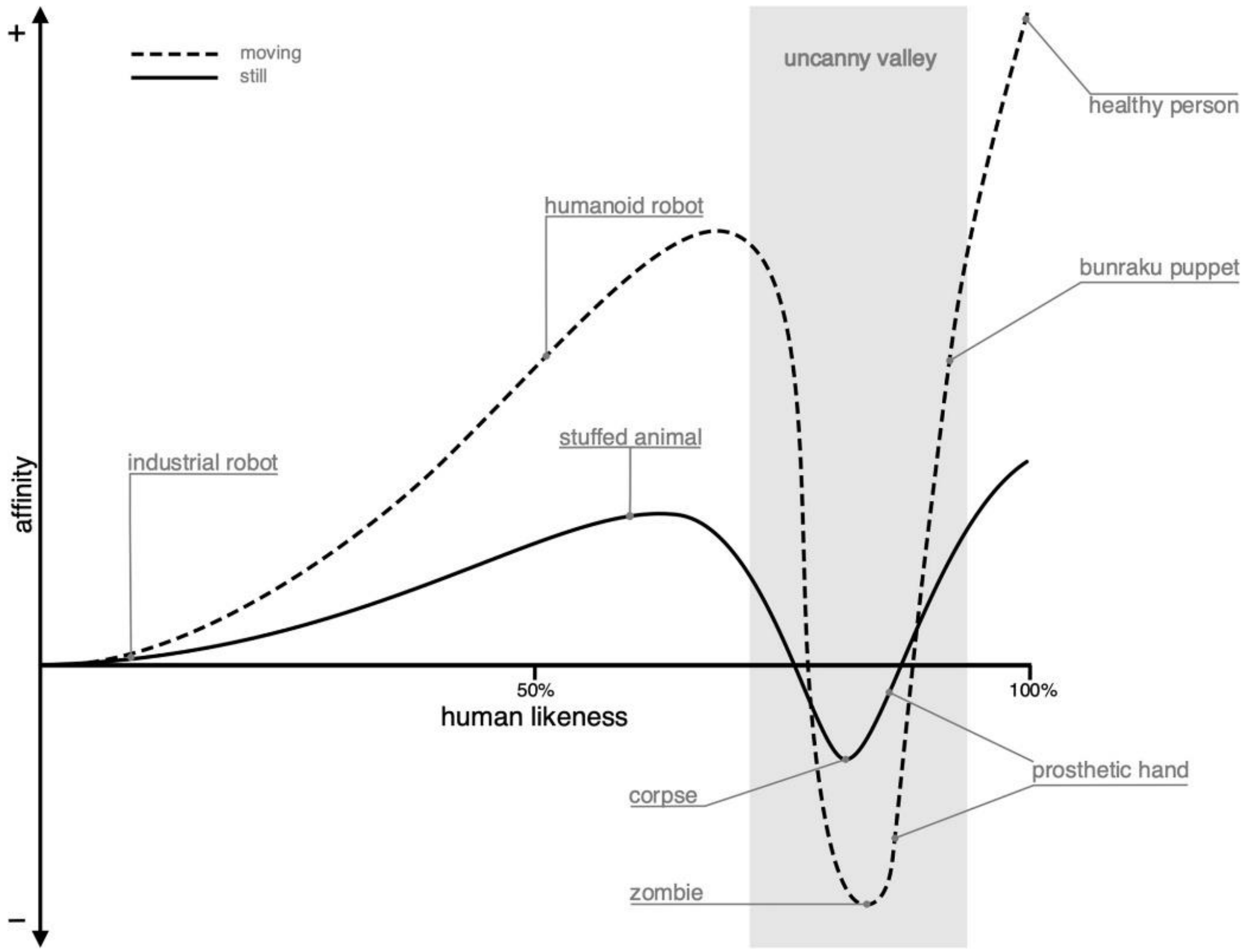

Fig. 1: Uncanny valley graph [3]

1.2 Research Aim

The aim of research is to create a novel system based on non-verbal cues and human-robot interaction for adults or kids who struggle with personality difficulties because of adverse experiences. This system focuses on three main cues for personality prediction i.e., a) Facial expression, b) Head pose and c) Body pose. For personality prediction the proposed system uses one to one human robot interaction and focuses on two other techniques, one is questionnaire and other is expert analysis.

1.3 Research Methodology

Keeping in view the robot assisted research in therapies and psychology studies NAO humanoid robot is the most used robot. Nao robot widely used in ASD (autism spectrum disorder) with psychological intervention [9]. A supervisory control system with adaptive closed-loop functionality has been implemented using NAO robot. Personality prediction system experimentation was conducted using human-robot interaction and questionnaire.

1.4 Contribution

This study focuses on predicting personalities using data from human-robot interaction, questionnaire, and expert opinion. Human robot interaction is a main part during feature extraction as big five inventory (BFI) questionnaire is used in interaction. In previous research, Proper features were not used for personality prediction [10]. Only three traits of big five model was measured [11].

Our research aims to combine all five traits of the Big Five model with non-verbal cues to predict personality using the humanoid robot NAO. Keeping in view that NAO humanoid robot was used in ASD (autism spectrum disorder) with psychological intervention [9]. Moreover, in each research multiple features combine for building dataset [11], [12], [10], and an algorithm extracts all the features simultaneously. Our study proposed a sequential method in which modules were built for feature extraction, aiming to address the lack of clarity in defining the correlation between traits and labelling of features using the big five model. As previously, labeling was done manually by the expert or psychologist and questionnaire [11], [10]. In our system, features are labeled with traits of the big five model using previous literature and confirmed by experts. Sequential execution of modules, with focusing on labels of all five traits for personality prediction reduces the computing cost and therefore results in efficient robot processing. Table 1 shows modules with their descriptions.

Table. 1: Modules used for Interaction

Human-Robot Interaction	Descriptions
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

1.5 Thesis Organization

This thesis is organized into eight chapters based on the research work done during MS. Chapter 1 is about “Introduction” that includes problem statement, research aim and research methodology. Chapter 2 is about “Literature Review” of personality theories, personality traits and questionnaires, feature extraction and features link with traits and social robots used in HRI. Chapter 3 is about “Emotion Estimation” that includes architecture, technique with pseudocode for analyzing emotion, network connection setup, subjects, and experiment setup. Chapter 4 is about “Head Pose Estimation” that includes architecture, technique with pseudocode for analyzing head orientation, network connection setup, subjects, and experiment setup. Chapter 5 is about “Body Pose Estimation” that includes architecture, technique with pseudocode for analyzing Body Pose, network connection setup, subjects, and experiment setup. Chapter 6 is about “Verbal Interaction” that includes architecture, technique with pseudocode how interaction will happen, network connection setup, subjects, and experiment setup. Chapter 7 is about “Personality Prediction complete system” that includes architecture, technique with pseudocode how each module will link with each other and work, network connection setup, subjects, and experiment setup. Chapter 8 is about the “Conclusion and Future Work”. It summarizes the work done and proposes future work.

CHAPTER 2

LITERATURE REVIEW

2.1 Personality

Personality is described as an individual's constant thoughts, feelings, and behaviors over time and in various contexts [13]. We use several words to describe other people and ourselves. My sister might be pleasant, and my brother might be an angry man. Descriptions vary because everyone has a unique personality. We think and act differently than other people do. In plain words, a person's personality governs their views, likes, and dislikes, ideas, actions and how they react in different circumstances [14]. The study of individual differences in views, feelings and actions that endure through time as a result of prior experiences is known as Personality psychology [15].

2.2 Personality Theories

Numerous personality trait theories are used to predict personality. Allport's' Trait theory, Cattell's 16 Factor personality, Eysenck's three Dimensions of personality, and Myers-Brigg's type Indicator (MBTI) [16] are among the most well-known. The Big-Five, on the other hand, is the most famous and commonly used. Extraversion, Openness, Conscientiousness, Agreeableness, Neuroticism are the five primary personality traits. Each of these has several sub-traits [17]. A Big-Five model is related to certain metrics. Costa and McCrae developed the NEO-Five factor inventory (NEO-FFI), a 60 items variant of NEO-FFI (1992). International Personality Item Pool Big-Five marker Scales (IPIP 50) contains 100 items presented by Goldberg (1992) after many years briefer version 20 items developed by Donnellan, Oswald, Baird and Lucas (2006). The Big-Five Inventory (BFI) 44 items were designed by john, Donahue, Kentle (1991) after many years 10 item version was developed in German & English by Rammstedt and John (2007). It has been employed in research [18] due to its flexibility.

2.2.1 Traits

Personality theories contend that individual human features may be utilized to predict human emotion, cognition, and behaviors. A trait is described as “a dimension of personality used to classify persons based on the extent to which they display a certain feature” [19]. These characteristics are regarded as the basic pillars of personality.

The Big-Five model qualities are prominent personality traits not just in social science research, but also in the study of human-robot-interaction [20]. To support these attributes OCEAN acronym is utilized, which stands for Openness, Conscientiousness, extraversion, agreeableness, and neuroticism [21], [22], [23], [24]. An overview of these characteristics is provided in Figure 2 [25]. Each trait as well as related sub-traits called facets are described in Figure 3. This is the original version, which was derived from McCrae & Costa (2006) and afterward utilized in many types of research, each trait also has an inverse [17]. Each trait has a severity scale ranging from low to high. Many sub-traits were altered or ignored in subsequent studies based on the study goal.

Factor	Description	High Value	Low Value	Factor
Extra-version	describes interpersonal behavior and is equated with enthusiasm	Sociable	Intro-vert	Extra-version
Agreea-bleness	is important in the context of interpersonal behavior	Cooper-ative, al-truistic	Com-peti-tive, suspi-cious	Agreea-bleness
Consci-entious-ness	describes the extent of self-control, accuracy and purposefulness of a person	Careful	Slov-enly	Consci-entious-ness
Neurot-icism	is also described as emotional lability or emotional strength and describes the individual differences in the experience of negative emotions	Unsta-ble	Stable	Neuroti-cism
Open-ness	describes the interest and the scope of dealing with new experiences and impressions	Inquisi-tive	Con-serva-tive	Openness

Fig. 2: Personality Traits with Descriptions [25]

Personality traits	Facets
Extraversion (E)	Talkative, a joiner, physically active, affectionate, passionate, fun-loving
Introversion	Reserved, seeking solitude (a loner), physically passive, quiet, sober, unfeeling
Open to new experiences (O)	Imagination, creativity, originality, prefer variety, curiosity, liberal
Traditionalist	Down to Earth, uncreative, conventional, uncurious, prefer routines, conservative
Conscientiousness(C)	Conscientious, hard-working, ambitious, well organized, persevering, punctual
Careless	Quitting, negligent, lazy, disorganized, aimless, late
Agreeableness (A)	Softhearted, trusting, generous, acquiescent, lenient, good-natured
Self-centered	Suspicious, ruthless, stingy, antagonistic, critical, irritable
Neuroticism (N)	worrying, temperamental, self-pitying, self-conscious, emotional, vulnerable
Emotionally stable	Calm, even-tempered, self-satisfied, comfortable, unemotional, hardy

Fig. 3: Personality Traits with Facets [McCrae & Costa (2006)]

2.2.2 Questionnaires

Questionnaires based on Liker Scales are utilized for personality evaluation [26], [19], [27]. These surveys allow humans to self-judgment of personality and the results have been confirmed through association with various ways of judgment [28], [12], [19], [29]. In most circumstances, psychologists provide judgement, except questionnaires. Psychologists provide judgment (cue validity & utilization) linked with Lens model [30], it's a trait accuracy approach. As previously noted, many surveys can be utilized, but NEO-FFI, IPIP and BFI are linked to the Big-Five paradigm. Why do we need a condensed questionnaire? Everyone is preoccupied with their jobs. Long surveys take time to complete, either a one-person survey (participant self-esteem) or when participants are needed to score other groups [31]. These surveys are used to collect data, which is then utilized for labelling, with or without the help of psychologists. Figure 4 shows the BFI questionnaire [28], [32].

ID	Statement	ID	Statement
1	This person is reserved	6	This person is outgoing, sociable
2	This person is generally trusting	7	This person tends to find fault with others
3	This person tends to be lazy	8	This person does a thorough job
4	This person is relaxed, handles stress well	9	This person gets nervous easily
5	This person has a few artistic interests	10	This person has an active imagination

Fig. 4: BFI 10-item questionnaire [28], [32]

2.3 Feature Extraction & Traits

According to psychopathology, face expression and body movement (whole body posture, head posture) have valuable applications in the study of emotions, depression, and personality. These are human behaviors that they show in different situations with verbal communication or without it. Research on non-verbal behavior exposed different channels of judgment. Observers sometimes observe a silent film or videotape, live user behavior, typescript, or voice [33]. Humans are quite adept at deciphering other's cues particularly when it comes to personality judgments [34]. Some cues are common in personality studies.

2.3.1 Head Pose

In human-to-human interactions, humans often utilize the head posture to convey their thoughts whether they want to converse or not and they agree or disagree. Glancing during a talk at the interaction partner indicates attentiveness but gazing elsewhere indicates apathy and anxiousness [35]. The gaze is connected to the head pose because measuring gaze with a robot camera requires high-resolution pictures and increases the computational cost [36]. Extroverts display positive connections with head movement and eye contact, indicating their sociability [37]. Neuroticism is associated with unstable emotions and a tendency to avoid eye contact by frequently shifting the head [37]. Openness is positively correlated with both eye contact and a desire for interaction, reflecting a person's openness to new experiences [37]. Agreeable individual tend to avoid eye contact and lower their head to show subservient [37]. Eye contact signifies confidence, while head motions express disapproval [37].

The roll, pitch, and yaw angles are used to predict head posture to determine the gaze score instead of utilizing eyes [10], [11] and gap between two adjacent frames was estimated [37], [10], It's referred to as Manhattan distance. Eye contact or eye gaze occurs when one person's attention is directed toward another person [38]. Another estimating approach is the direction magnitude pattern (DMP), which calculates the direction and magnitude of each pixel concerning its neighbor's resultant force [11], [39]. ROI is recognized using the OpenCV version of the Viola and Jones Haar cascade technique [40], and the Intraface library is used to compute head angles roll, pitch, and yaw [12]. Hough transformed [41] was also utilized to extract head posture and its parameters helped in detecting lines placed in the picture. Head pose is a widely used cue as a signal in group studies. In [42], the face is estimated using a particle filter and then for head movement analysis optical flow vectors were calculated for two frames within the face region using an optical flow algorithm. The features for each participant were recovered by binarizing vectors using an automated threshold.

2.3.2 Body Movement

In studies, arm gestures and body movement are assessed and even the tiniest change in the body may be measured. Waving, folded arms, pointing, and other hands or arm actions as do postures like thinking posture, erect posture, and crouching posture send messages. Except for head motions, all movements are considered body motions. Neuroticism correlates with closed arms and thinking posture [37]. Extroverts display more expressive body posture [37] . Openness is reflected in self- assured or open postures [37]. Agreeable people minimize bodily movements and adopt an open attitude [37]. Conscientious people exhibit an open or closed-arm posture with a change in proximity to communicate their thoughts [37].

Body activity is detected by simple motion differential [42] since the backdrop is motionless. Except for head motions, all movements are considered body motions. After converting each image to greyscale to quantify body activity, the difference between the images was found. Body pose is determined in [12] by recognizing skeletal joints on the upper body using the approach described in [43]. The same method is used in [11], body motions are identified by employing upper-body skeletal joint angles. Even the slightest change in the body is monitored and if it reaches a certain threshold then movement occurs otherwise nothing happens. The body motion is then extracted using two photographs. Joint angles were calculated after comparing the original and warped images, images suggesting that the skeleton has been rotated in reference to the initial skeleton [10]. Skeletonization can be used to identify any changes in the hand, elbows, shoulders, and other parts of the body during movement.

2.3.3 Facial Expressions

Facial expressions are any facial muscle action, such as smiling and yawning, as well as expressions with the eyes and brows such as winking, scowling, and so on. The study of facial expression focuses on emotions [33]. People appraise effective states based on indicators, such as drooping eyebrows indicating anger, and how individuals depict their own and other personalities across cultures [44]. Trait's assessments were based on these impressions [30]. formed the foundation for trait's evaluations [30]. The research done by D. Keltner [44] explains the relationship between facial expressions and the five factors of personality used by Big-Five Model. A smile is a symbol of happiness, friendliness, and positive emotionality for extroverts. Neurotic people experience negative emotions such as fear, rage, and anxiety as a result of their unstable emotions. Agreeableness is associated with laughter and positive social contact since it is connected to friendliness, compassion, and warmth. Conscientious people laugh for some reason, and they have regulated smirk. Negative emotions have a weak association with conscientiousness. Openness to experience is positively associated with the laugh these individuals want to connect and smiling is a form of communication.

Basic emotions were distinguished using convolution neural networks [11]. Five techniques for emotion recognition were compared in [45], using four fundamental emotions (happiness, sadness, anger, and fear). The deep learning technique AlexNet CNN for prediction, FER-CNN for extracted faces retrieved using the Viola-Jones technique [40], Affdex CNN, and convolution neural network (CNN) compared to differentiate six basic emotions. SVM and MLP ANN classifiers were employed with HOG features extraction, utilizing facial landmarks supplied by OpenFace for detection. The Affdex SDK and convolution neural network (CNN) were then compared to differentiate six basic emotions [46]. A review of deep learning for emotion identification is presented in [47]. From the aforementioned data, well-known techniques for extracting facial expressions and emotions may be deduced.

2.3.4 Paralanguage

Paralanguage gives speech rate (the number of words in a specific timeframe), voice break (the number of pauses between sentences), frequency (voice pitch), pitch variance, amplitude (voice loudness or intensity), and variation in amplitude [30].

Research on the perception of various verbal cues has revealed that individuals rely on voice and speech to make an impression on others [48], [49]. Prosodic cues also carry emotional information. It also reveals personal intentions for how one intends to appear to others. The big-five factors that are related to communication [50], Extroverts are good communicators and use language signals to express intentions. A neurotic person has unstable emotions and refuses to communicate. Agreeableness indicates generosity, sympathy, etc. whereas aggressiveness is the converse. Pleasant people don't adopt aggressive speech to defend their point of view. The depth, creativity, and complexity of one's thoughts are measured by openness. It has been linked to IQ and verbal intelligence [51], with those who have this facet regarded as expressive, witty, and verbally proficient. Goal-oriented and self-efficient persons are more likely to be conscientious. These folks attain their objectives through aggressive communication.

Linear domain frequency and Mel Frequency Cepstral Coefficients were collected [52] for prediction, and k-nearest neighbor (KNN) and Support vector machine (SVM) were used to classify speaker features. The speech feature extractor OpenSMILE was used to extract acoustic features from audio data [53], which were then combined with head motion and communication abilities as well. The classification techniques employed were SVM, random forecast, Naïve Bayes, and decision tree algorithms. Pitch and vitality of the voice, Mel-frequency cepstral coefficient was extracted in [10], and auto-correlation function was employed to monitor pitch before calculating the average of short-term energy. After partitioning frames into short-time frames, the Mel-Frequency was computed by applying the Fast Fourier transform to each frame. In this case, CNN used audio to deduce personality traits.

2.4 Social Robots

Human-Robot-Interaction (HRI) is an exceedingly new topic that has gained a lot of interest in recent years. Robots are rapidly being created for global applications such as eldercare, rehabilitation, and robot-assisted treatment, and many more. The purpose of social robots is to engage with people utilizing both verbal and non-verbal cues. Many social robots feature anthropomorphic (humanoid) or animal-like appearances, and individuals favor anthropomorphic social robots [54]. Many social robots have been developed over the years such as Geminoid, Pepper, Nao, Roman, KASPAR, Aibo, Paro, kismet, Keepon, and others [55].

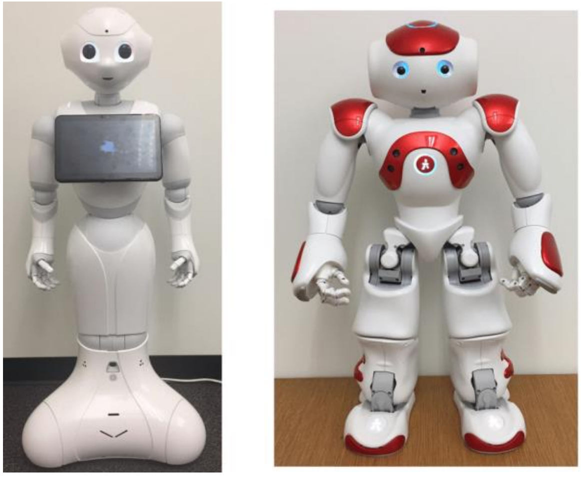

Fig. 5: Pepper (Left side) & NAO (Right side)

NAO and Pepper, both of which were designed by “Soft Bank Company”. The robots [56] can be seen in Figure 5. Emotions [46], Autism [57], tutoring [58], path planning [59], therapies [60], tourism [61], and a variety of other research have employed Nao. Pepper operates as a teacher at home [62], in shopping malls for amusement [63], exhibiting emotions [64], autonomous navigation and personalized interaction [65], tourism guide [61] and many more sectors, just as the Nao.

Many robots are utilized in personality research. NAO was employed [12], and participants have a cooperative engagement with each other and NAO. Using the iCub robot [19] single extraversion trait was measured. The robot began interacting with humans to give a paper toy. A ROBIN humanoid robot was used [11], for the analyze personality traits in various circumstances. Using pepper [10] features extraction was done, and the robot was interacting with a person at the time. RoBoHoN [29] was used to measure personality by recognizing verbal features. Aside from that, iCat, PeopleBot, Meka are employed in numerous personality research.

2.5 Datasets

2.5.1 Head Pose Estimation Datasets

The previous few years have seen the evolution of many datasets that are now widely accessible. Several datasets have been created from 2008 to 2018. Nevertheless, outdated databases did not include the roll angle. The rotation of a rigid body with respect to a fixed coordinate frame is provided by several datasets using Euler angles. Both intrinsic and extrinsic rotation angles exist. There were just three datasets created in 2017 and 2018. The first is SynHead [66], a synthetic dataset with the head orientation data of 10 persons. 5 males and 5 females. 70 movements were derived from 510,960 frames. Every Euler angle was present. Researchers obtained 24 movements from BIWI and 26 from the ETH dataset. Next, using Kinect and Softkinetic sensors, 20 further movies of 11 men and 2 women were captured.

The second dataset is SASE [67], which contains RGB and depth pictures captured by the Kinect 2 camera. Data from 50 respondents, ranging in age from 7 to 35 years, were collected. Of those, 32 were male and 18 were female. They collected 30,000 frames. The dataset could be utilized for emotion identification because all participants displayed a variety of facial expressions throughout all rotation angles. Third, the largest dataset VGGFace2 [68], with 3.31 million photos. It was built using photographs from Google Image Search and covers all three rotations as well as significant variances in posture, age, etc.

2.5.2 Body Pose Estimation Datasets

The popularity of 3D pose estimation has increased recently, however, there are several difficulties with it [69] such as varied inputs (difficult to acquire merely posture data from images owing to objects, shadows, etc.), numerous humans (identifying 3D poses of many persons is tough) and other (annotating that kind of data is a problem and that kind of datasets are less). For 3D pose estimation, several datasets were created between 2010 to 2018 [69], just as many 2D pose estimation datasets were created between 2010 to 2019 [69], however between 2017 to 2019, only three datasets were created, and they are all for multiple people pose estimation.

The first is AI challenger [70], which mostly consists of three large-scale photographs with few human subjects. For complete body posture, there are 14 key points. It is not for the photos that are cluttered with people. The second dataset is PoseTrack [71], [72], which has two versions. The first was created in 2017 and uses 20 videos for testing, training, and validation sets and contains 15 full-body key points. The second was created in 2018 and uses 292 videos for training, 50 videos for validation, and 208 videos for a test set with 15 full-body key points. The third is CowdPose [73], which is obvious from its name as it is made by extracting photos of crowded scenes. For the whole body, it has 14 essential key points. There are 10,000 photos for the train set, 2000 for the validation set, and 8000 for the test set.

2.5.3 Emotion Analysis Datasets

A large dataset with tagged photos is needed for accurate and effective emotion recognition. Basic emotions are tagged in every dataset for emotion identification. Datasets are crucial to machine learning and deep learning. Images may be converted to pixels or annotated photos can be utilized to create a dataset for emotion identification, however images are most advised. There are many datasets, but three are famous. The first is KDEF [74], which was released to the public in 1998 but is still accessible. It has 4900 samples and 7 annotated classes. The second most popular dataset gathered from the Google Image Search API is FER2013 [75]. It is made up of 35,887 photos with seven categories for emotions. After that, FER+ [76] was put forward with 35,485 photos and 8 emotion classifications. The next is CK, which has 486 photos with 6 emotions classified, followed by CK+ [77], which is an enhanced version and has 593 images with 8 emotions labeled.

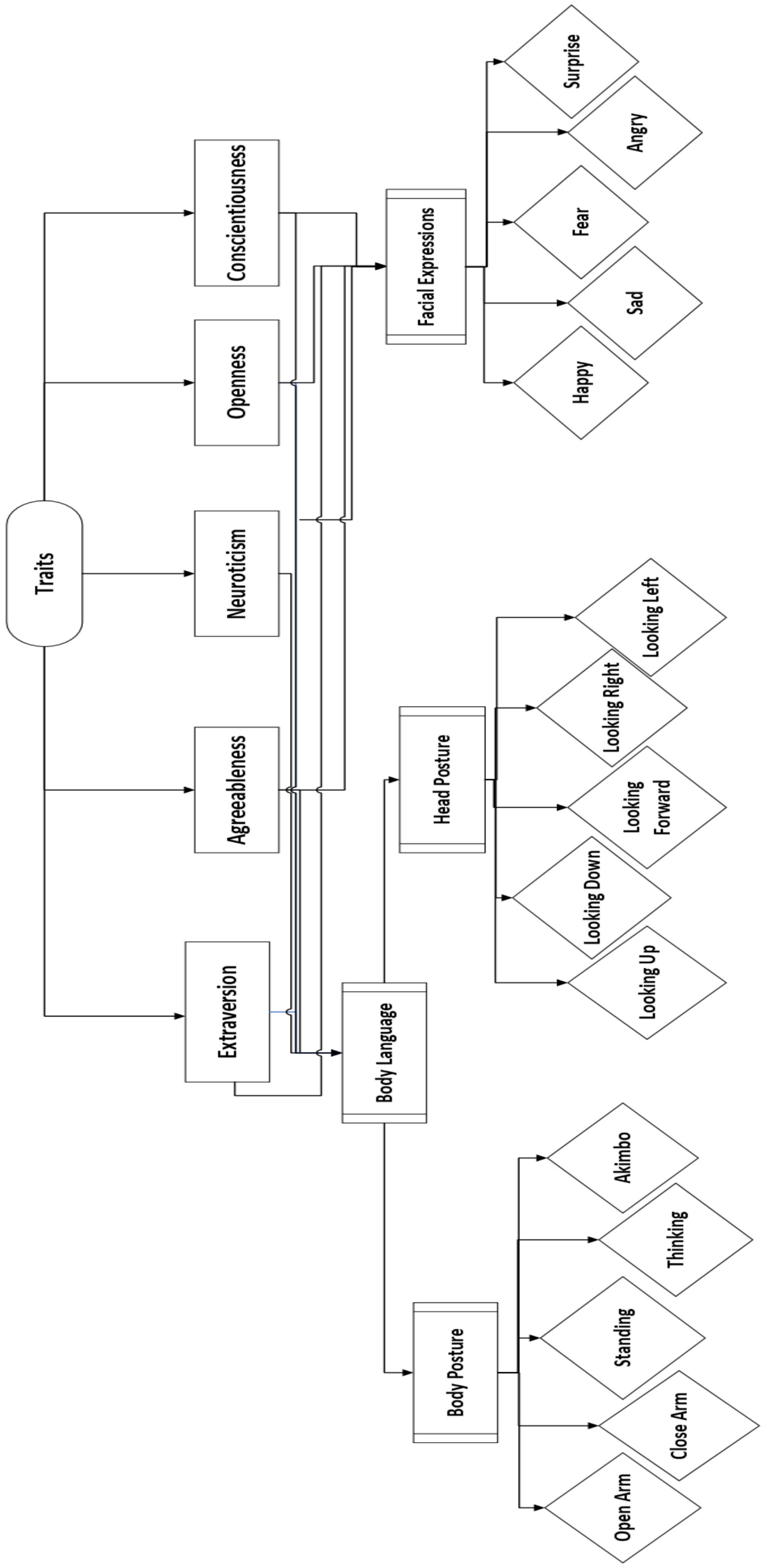

Fig. 6: Complete Structure of Personality Traits and Features

CHAPTER 3

PERSONALITY PREDICTION COMPLETE SYSTEM

Personality is lasting interpersonal events and the behaviors based on them [78]. Non-verbal clues are utilized in literature to interpret behavioral manifestations of ideas, feelings, and attitudes [79]. Each action taken by a person is considered behavior. Certain actions have meaning. Because behavior is something that a person expressly performs, it may be seen [80]. Yet, habitual conduct does not cause habits [81]; instead, habits are the result of intentional activity.

Due to the complexity of behavior, there are four ways to access social or personality psychology: direct observation, informant reporting, self-reporting, and trace measurements [82]. Since self-reporting techniques in the form of questionnaires are utilized, there are biases or reporting inaccuracies [83] despite their low cost. Psychologists, counselors at educational institutions, and in certain cases parents, give informant reporting or direct observation. Researchers that investigate social behavior and personality should include behavior evaluation [80]. Quantifying behaviors alone is not sufficient; they must be translated. Social and personality theories use behaviors for translation. Recognition of emotions or attitudes can be distinguished from behavioral clues [84]. Behavioral evidence includes head motions, leaning of the torso and trunk, eye contact, and gesture [85].

3.1 Humanoid Robot predicting human Personality

The proposed system for personality prediction utilizes the Big-Five personality model, comprising five traits: Extraversion, Neuroticism, Agreeableness, Openness and Conscientiousness [86], [17]. Traits related to features architecture are shown in Figure 6. These personality traits are assessed utilizing nonverbal cues such as facial expressions and body language. Five key characteristics closely related to personality prediction are considered after consulting with the psychologist. The proposed system uses all the nonverbal cues to predict personality and link it with the features. Each of the five traits of the big five model will be evaluated using these features.

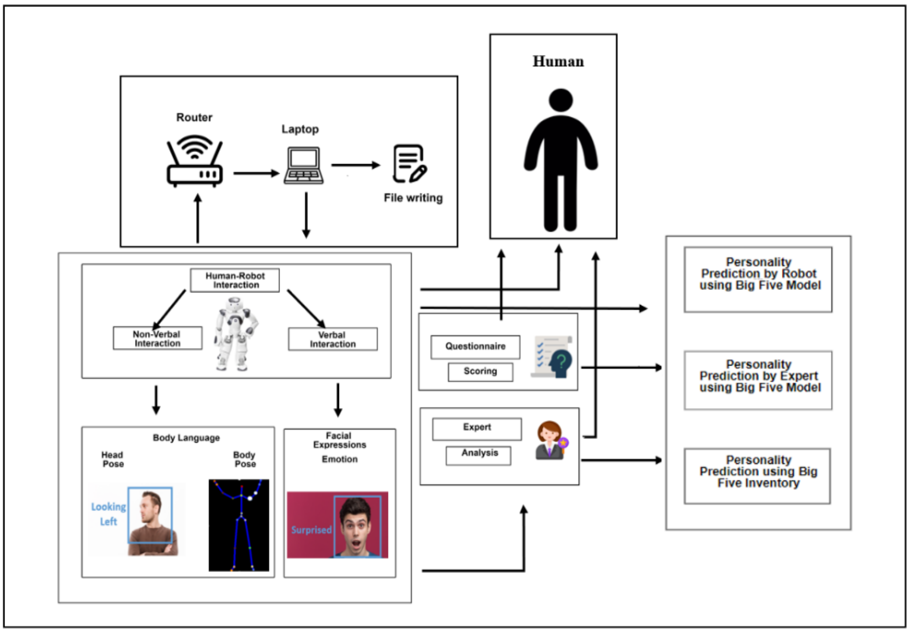

Fig. 7: Architecture of the proposed model

The architecture is shown in Figure 7. The architecture utilizes the Big Five Inventory (BFI) questionnaire, verbal interaction using the BFI questionnaire, and expert analysis for personality prediction. These three methods are employed to predict personality traits. Figure 8 shows the system flow chart including face detection, emotion detection, head pose estimation, skeletonization for pose estimation, data storage, and personality prediction. Each module is explained in the sections below with testing results.

3.1.1 Verbal Interaction (Module 1)

Human-robot interaction is essential for effective communication between humans and robots. It involves communicative acts aimed at influencing the interacting agent, often resulting in unintended actions[87]. Text-to-speech systems require a framework and conversation structure to generate speech [88]. Two types of human-robot contact exist: distant interaction, where the human is physically separated from the robot and proximate [89], where both the person and robot are present together. This system utilizes proximate human-robot interaction.

The system utilizes a voice recognition library and the Nao robot text-to-speech API. The robot is given a predetermined questionnaire (BFI), a speech recognition library is used to access laptop or a wireless microphone for sound recognition.

Participants were asked to respond to each question with a yes or no. If there is no response within 3 seconds, the robot proceeds to the next question. By minimizing noise and taking necessary precautions, favorable outcomes were achieved. Figure 8 shows the verbal interaction flow.

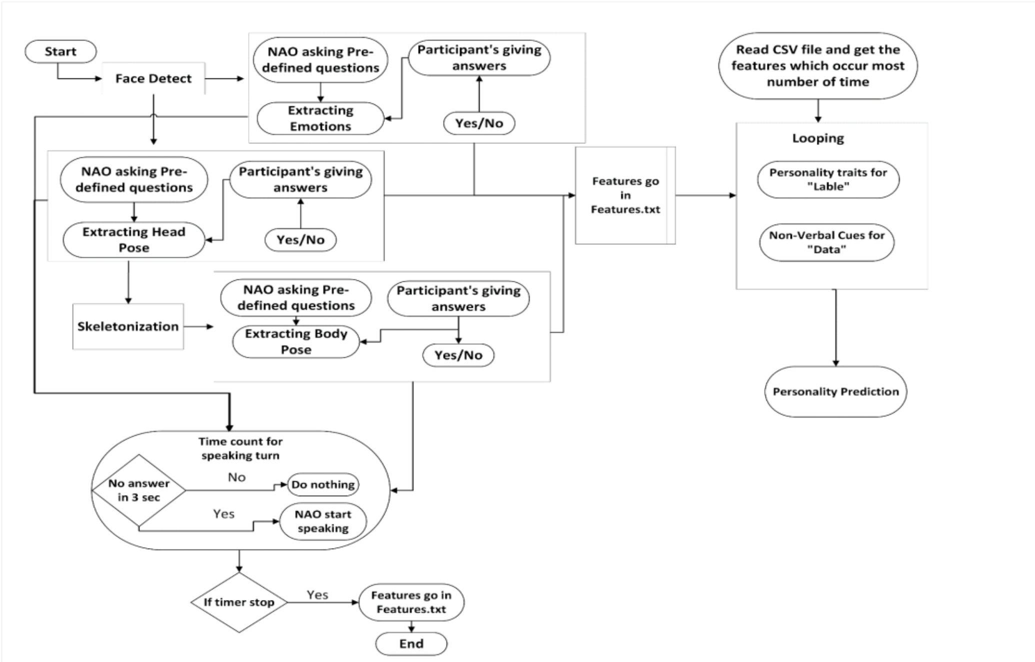

Fig. 8: System flowchart for complete architecture explaining personality prediction based on Human-Robot Interaction (HRI)

Table. 2: Model Training Formulas for emotion recognition using robot

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

3.1.2 Facial Expression Estimation (Module 2)

The growing need for automated emotion recognition systems has led to significant research in the field of human-computer interactions [90]. Emotion recognition can be achieved through various modalities such as speech, text, facial cues, and EEG-based brain waves [91]. Two techniques for emotion recognition: unimodal and multimodal. Unimodal approaches evaluate emotions using a single modality (e.g., speech, EEG, facial expressions), while multimodal approaches combine multiple modalities for emotion estimation [92]. This research focuses on five universal emotions: Happy, Sad, Fear, Angry, and Surprised, as presented by psychologist Paul Ekman [93]. Five universal emotions are used in this research: Happy, Sad, Fear, Angry and Surprised. FER+ [76] dataset is used, focusing on five relevant categories for emotion recognition.

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. The fully connected layers aid in picture classification, while the convolutional layers extract essential image characteristics. The convolutional operator moves over the image, extracting features pixel by pixel. 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 mathematical model for training CNN. The model accuracy is 91%. Figures 9 and 10 show the plot and confusion matrix of it. After training the model, the next task was to detect a person's face using the Haar Cascade frontal face detection model, which employs edge and line detection techniques proposed by Viola and Jones [94]. Live NAO robot camera captured frame-by-frame input, displaying emotion labels. Table 3 shows the model testing results; test number 5 and 9 indicate incorrect findings.

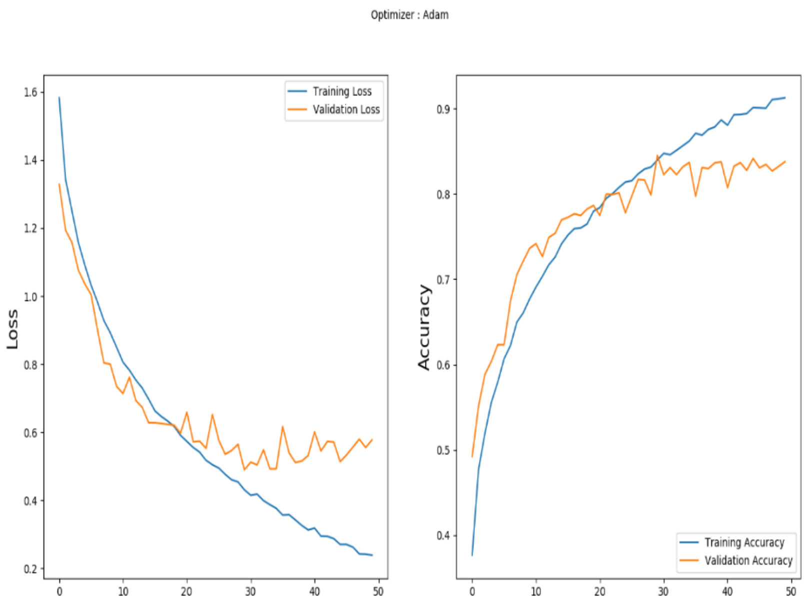

Fig. 9: FER + Accuracy & Loss Curves

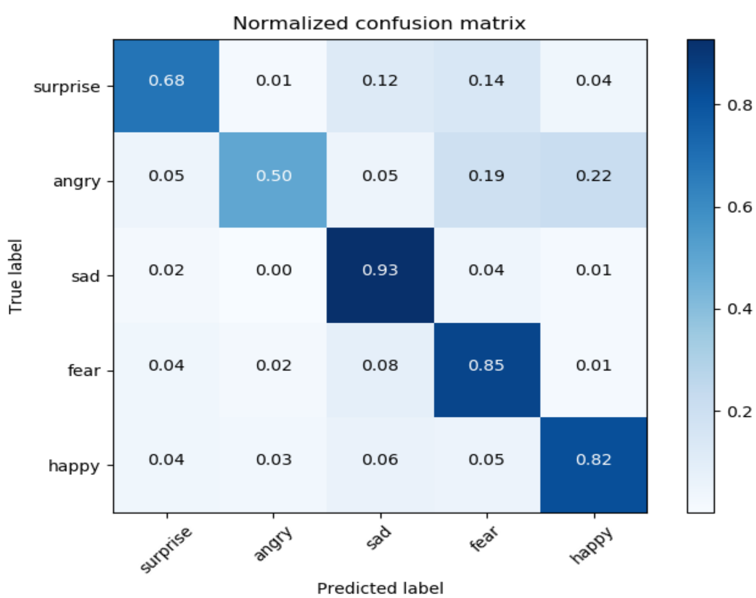

Fig. 10: FER + Confusion Matrix

Table. 3: Result of Emotion Recognition

Test No.	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

3.1.2.1 Pseudocode

Model Training

1. CNN Architecture
   a. Input layer with input images: IƐR^(a=height,w,1)
   b. Convolution layer with filters (kernel size, activation function):
      B1= w1 * I +c1, S1= ReLU (B1)
   c. Pooling layer
      A1= max_pol (S1, pol_size = (a1, a1)
   d. More Convolutional and Pooling layers (as required):
      B2= w2 * a1 +c2, S2= ReLU (B2)
      A2= max_pool (A2, pool_size = (a2, a2)
   e. Flatten layer (2D features to 1D)
      f= flatten (mn)
   f. Output layer (Softmax function and number of classes):
      Bn+m = wn+ m * S_n + m-1 + c_n +m, S_n +m = Softmax (Bn+m)
2. Loading Training and Test/validation sets:
   a. Labeled images of different emotions:
      (X_train, y_train), (X_test, y_test)

3. Preprocess the images of both test and train dataset.
    a. Rescaling, Size, Color Mode and Class mode.
       rescale = 1. / 255
       target_size = (48,48)
       color_mode = greyscale
       class_mode = categorical
4. Model Training
    a. Loss function
       LF = -1/m * sum (y_train * log (S_n +m) + (1- y_train) * log (1- S_n + m))
    b. Adam optimizer
       w, c = init_para ( )
         for I in range (epochs):
    c. Update parameters
       w = w – alpha * dw
       c = c – alpha * db
    d. Forward and Backward propagation
    e. Compute cost
       C = cost (S_n + m, y_train)

Emotion Prediction

1. Call model file and weight file.
2. While (live_video) {
       I ← extract_Image( )
       If (detect_F(I)) {
           face ← crop_F (I) }
         Emo ← analyzeFace(face)
           if (Emo) {
                   label emo (Emo)
                   save emo (Emo) }}
3. Threading with verbal questionnaire (both process runs parallel).

3.1.2.2Big five model relation with Emotions

The third task was linking the emotions with personality prediction system. An individual's facial expressions during engagement or communication are more significant. Traits correlated with emotions are related 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 events. Table 4 shows the correlation of facial emotions with traits of big five model [30], [11], [95], [96].

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	+	-	-	-	-

3.1.3 Head Pose Estimation (Module 3)

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[97]. Roll, pitch, and yaw are the only three degrees of freedom (DOF) that the human head may have in relation to the camera [98], as shown in Figure 11. Head motion is often studied using head nodding and shaking [99]. In this research, five main head positions (looking ahead, up, down, left, and right) are employed. Pose estimation in computer vision refers to determining the orientation of an object relative to the camera, and it is commonly used to estimate head poses.

In this study, the Geometric Method is employed for head position estimation, utilizing facial landmarks and projective geometry. The first step involves establishing a reference frame. Subsequently, the perspective-n-point problem (PnP) is solved. The human head has three degrees of freedom (DOF) in relation to the camera: roll, pitch, and yaw [100]. Euler angles (roll, pitch, and yaw) are utilized to reconstruct the six DOF of the reference as the camera moves between 3D points. This allows for the determination of translation and rotation. Following that, the dlib library was utilized to detect faces and landmarks. By leveraging the 3D face model, 2D reference matrix, and camera matrix, the PnP equation was solved to obtain the image rotation and translation. The PnP rotation and translation matrices were computed. The camera's focal length was calibrated as it is an intrinsic parameter. Euler angles were extracted from the obtained data. The mathematical model for finding translation, rotation matrix and Euler angles is shown in Table 5.

Table. 5: Mathematical model for Head Pose

Purpose	**Mathematical Model**
Translation & Rotation Matrix	$$s\begin{bmatrix}u\\v\\1\end{bmatrix} = \begin{bmatrix}f_x & \gamma & u_0\\0 & f_y & v_0\\0 & 0 & 1\end{bmatrix}\begin{bmatrix}r_{11} & r_{12} & r_{13} & t_1\\r_{21} & r_{22} & r_{23} & t_2\\r_{31} & r_{32} & r_{33} & t_3\end{bmatrix}\begin{bmatrix}x\\y\\z\\1\end{bmatrix} \quad (1)$$
Euler Angles	$$\begin{bmatrix}x\\y\\z\end{bmatrix} = R_z(\psi)R_y(\theta)R_z(\phi)\begin{bmatrix}X\\Y\\Z\end{bmatrix}$$ $$= \begin{bmatrix}cos\psi & -sin\psi & 0\\sin\psi & cos\psi & 0\\0 & 0 & 1\end{bmatrix}\begin{bmatrix}cos\theta & 0 & sin\theta\\0 & 1 & 0\\-sin\theta & 0 & cos\theta\end{bmatrix}\begin{bmatrix}1 & 0 & 0\\0 & cos\phi & -sin\phi\\0 & sin\phi & cos\phi\end{bmatrix}\begin{bmatrix}X\\Y\\Z\end{bmatrix}$$ $$= \begin{bmatrix}cos\theta cos\psi & -cos\phi sin\psi + sin\phi sin\theta cos\psi & sin\phi sin\psi + cos\phi sin\theta cos\psi\\cos\theta sin\psi & cos\phi cos\psi + sin\phi sin\theta sin\psi & -sin\phi cos\psi + cos\phi sin\theta sin\psi\\-sin\theta & sin\phi cos\theta & cos\phi cos\theta\end{bmatrix}\begin{bmatrix}X\\Y\\Z\end{bmatrix} \quad (2)$$

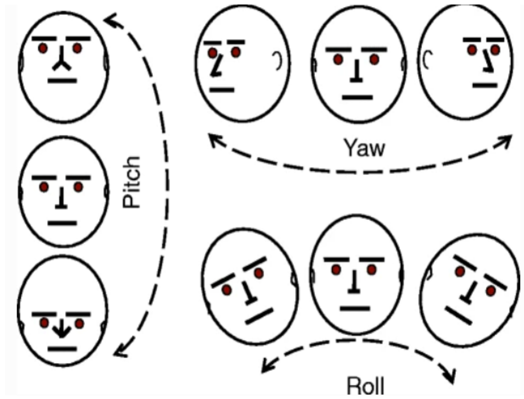

Fig. 11: Head Euler Angles [98]

Previous studies utilized six face landmarks [101] for head posture estimation, while our study employing fourteen 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 recognition of 68 landmarks [102]. 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 [103]. Using this in our study poses are distinguished. Frame-by-frame input from NAO robot live camera displayed head pose labels. Testing results are presented in Table 6, with incorrect findings on test number 1 and 5.

3.1.3.1Big five model relation with Head Pose

The next task was linking head poses with personality prediction system. Head posture involves looking forward, looking up, looking down, looking left, and looking right; traits correlated with head posture: The most frequent posture used when interacting is facing forward, whereas facing right is the least used. When individuals want to connect or communicate, they look at the other person. 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 are presented in Table 7 [30], [11], [104], [105].

Table. 6: Result of Head Pose Estimation

Test No.	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. 7: Big-Five Model Correlation with Head Poses

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

3.1.4 Body Pose Estimation (Module 4)

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 coordinate for each joint [106]. Basic poses: standing, open arms, close arms, akimbo and thinking are selected. First task is skeletonization using MPII model [107], a pre-trained model based on Caffe by the Openpose team was used which consists of 15 points for a single person. 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 [108] to determine joint angles. Mathematical models for calculating distance and joint angle are shown in Table 8.

Data from 20 subjects with heights ranging from 5'1" to 6'3" was collected. Based on the data angles threshold was established for each pose. Frame-by-frame input was captured using NAO robot live camera, which displayed body pose labels. Table 9 shows the testing results with incorrect findings on test number 1 and 3.

Table. 8: Mathematical model for Head pose

Purpose	Mathematical Model
For Euclidean Distance	$Dis = \sqrt{(b-a)^2 + (d-C)^2}$ (3)
Law of Cosine	$\theta = \arccos\left(\frac{ab \cdot cb}{\lvert ab \rvert \cdot \lvert cb \rvert}\right)$ (4)

3.1.4.1Big five model relation with Body Pose

The next task was linking body pose with personality prediction system. For Body posture open arms, close arms, standing, thinking, and akimbo poses are used. Table 10 shows the link between the "big five" model traits and the body postures [30], [11], [109] and [110]. Typically, an upright standing position with 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 [110], which can be used to display dominance or be adopted casually.

Table. 9: Result of Body Pose Estimation

Test No.	**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. 10: Big-Five Model Correlation with Body Poses

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

3.1.4.2 Pseudo codes

A. For Verbal Interaction

```
Initialize "ALTextToSpeech" module of Nao robot.
Initialize Speech Recognition library in python.
Robot will ask pre-defined questions:
        for Question ← (Questions)
            say (Question)
Initialize laptop or wireless microphone for speech recognition;
          Microphone ()
          Recognizer ()
Answer recognition and move to next question:
        if
             audio = listen (source)
             listen timeout=3
             Question++
        elif answer ← ("yes", "yeah", "ya")
             Question++
        elif answer ← ("no", "na", "never")
        Question++
```

B. For complete system

```
START
// For Emotion
Launch verbal interaction file
Start_time = time()
Call model file and weight file.
While (live_video) {
     I ← extract_Image( )
  If (detect_F(I)) {
     face ← crop_F (I) }
     Emo ← analyzeFace(face)
     If (Emo) {
          label emo (Emo)
          Save emo (Emo) }}
  If time ( ) - start_time > 20:
        Exit( )
```

```
// For head pose
Launch verbal interaction file
Initialize K(camera_matrix)
Initialize d (Distortion_Coefficient)
Obtain rotation and translation vectors:
        T= [R1,  R2 ,    R3  ,  t11]
           [R11, R12,  R13,  t12 ]
           [R21, R22,  R23,  t13]
Calculate Euler angles
```

```
Set the threshold.
 Start_time = time()
 While (live_video) {
     I ← extract_Image( )
     If (detect_F(I)) {
         face ← euler_angle (I) }
         headpose ← analyze_euler_angle(face)
        check conditions with threshold
        label HeadPose (headpose)
        Save HeadPose (headpose) }
      If time ( ) - start_time > 20:
           Exit( )
```

```
// For body pose
Launch verbal interaction file
Start_time = time()
Initialize the pretrained MPII Pose model
Initialize camera generate blob from the image using DNN model
while (live_video) {
     If prob > threshold
     cv2.circle(frame)
    Find distance between the required joints:
      ab = P1 - P2 & bc = P3 - P2
    Law of cosine:
      cosine_angle = (ab x bc) / (eucladian_distance(ab) * eucladian_distance (bc))
       angle = arccos(cosine_angle)
    Set min and max threshold for each feature (Rshoulder,Relbow,Lshoulder,Lelbow) for each pose.
     Check conditions
                If (bodypose) {
                      label BodyPose (bodypose)
                      Save BodyPose (bodypose) }}
       If time ( ) - start_time > 20:
           Exit( )
```

```
Read features.csv file.
Loop through rows and find the features which occur maximum number of times:
              counts = {}
              for row in rows:
             Emotion = max (counts, key=counts.get)
             a = Emotion
             Head pose = max (counts, key=counts.get)
             b = Head pose
            Body pose = max (counts, key=counts.get)
            c = Body pose
Take a, b, c to make conditional statements
Check the conditional statements:
            If trait ← statement
```

launch a window
print a, b, c , trait

Initialize "ALTextToSpeech" module so that Nao robot will say the predicted trait:

say (trait)

END

3.2 Features Labeling & Traits Correlation

The features sequences were named based on previous literature related to the traits of the Big Five model [30], [11], [96], [109], [104], [105], [110], [95]. These sequences were verified by a psychologist/expert. The number of possible sequences for each trait was determined based on positive correlation or negative correlation. Positive correlation indicates a positive association with a trait, negative correlation indicates a negative association, and zero represents no correlation. The correlation between certain traits also aligns with findings in [111]. Table 11 shows the correlation between traits.

Table. 11: 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**

3.3 Personality Prediction: Questionnaire & Expert Analysis

This research utilizing the 44-item BFI (Big Five Inventory) questionnaire [112], [113], [114], to assess participants personality traits according to the big five model. Participants were asked to fill in a questionnaire and their personalities were identified based on the responses. The participant's personality was revealed by an expert after analyzing the human interaction with a robot and data that was taken during the interaction of 16 participants.

3.4 Hardware

Different robots were used to study personalities: iCub robot [19] for predicting extraversion trait of personality, ROBIN [11] humanoid robot for analyzing personality characteristics, pepper [10] for features extracting for personality detection, RoBoHoN [29] robot was used to assess personality by identifying verbal attributes. Among all, NAO is considered as the most popular robot for interaction as participants interacted cooperatively with NAO [12]. Thus, Nao was selected for this system. utilizing its camera for feature deduction and "Say Text" module for human-robot communication.

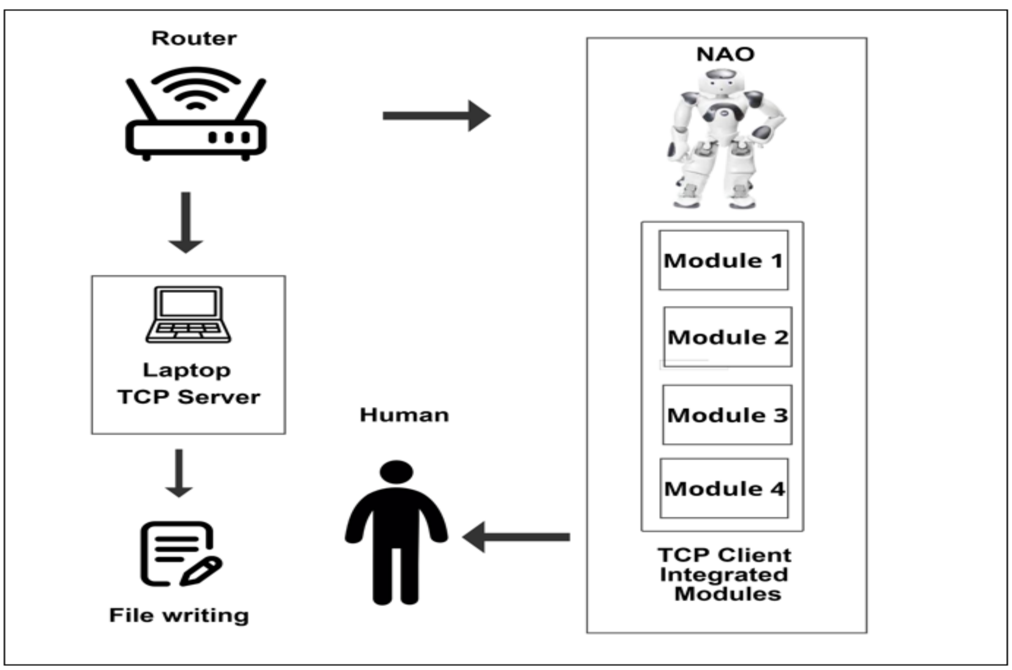

Fig. 12: Network diagram for processing of different modules

3.5 Networking Protocol

Figure 12 depicts the networking protocol or connection-building process. Robot was interacting verbally while performing feature extraction modules. The laptop includes a transmission control protocol (TCP) server. The robot was operating modules that were TCP integrated. They were transmitting data to the laptop in real-time. The data was being entered through a file writing technique into a file. Each module underwent this entire procedure once, with the data being stored in a single file.

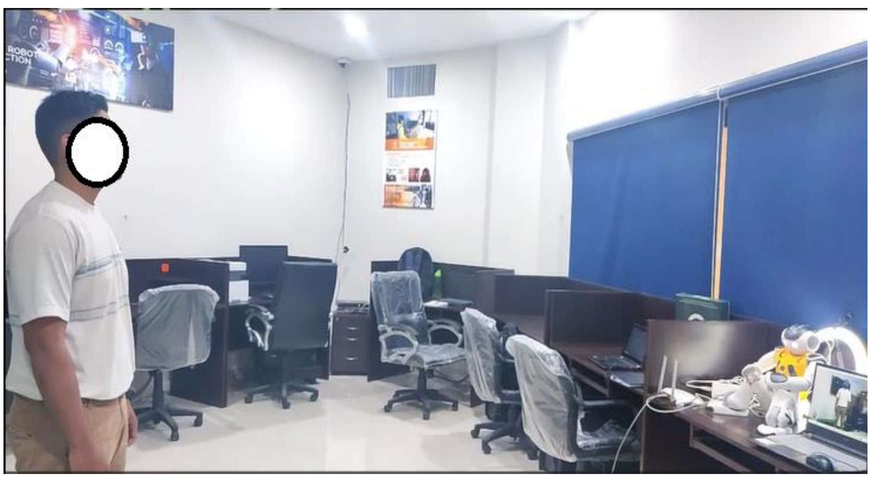

Fig. 13: Engagement of a participant with the robot

Fig. 14: Labelling of different modules using NAO camera during a human-robot interaction.

CHAPTER 4

MATERIAL & METHODS

4.1 Subjects

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

4.2 Experimental Setup

Figure 13 shows the environment setup of the interaction. 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.

4.3 Experimental Design

The robot and laptop were connected via a router and an Ethernet wire. Following the SOLER [115] 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 NAO robot upper camera with the modules running sequentially.

The facial expressions module begins with verbal interaction and lasts for 40 seconds, with data stored in a file. The second module starts with face recognition, followed by the collection and storage of head positions in the same file as the emotions, also lasting for 40 seconds. The final module involves skeletonization of the entire body, joint extraction, and angle calculation, with the resulting postures saved in the same file. This module runs for 40 seconds. Personality prediction will be performed using the accumulated data.

4.4 Data Processing

For verbal interaction NAO robot API, "ALTextToSay" was used and for participant speech recognition laptop 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 file which was readable.

CHAPTER 5

RESULTS & DISCUSSION

5.1 Results

5.1.1 Personality Prediction System (PPS)

The NAO robot camera recorded real-time data as the modules ran sequentially, displaying labels for emotion prediction, head position estimation, and body pose estimation. Figure 14 shows the result. These labels were saved in a file. At the end, an interface was shown, presenting the weightage of features observed during the experiment and the predicted personality based on those features. A graphical user interface (GUI) was used to present this information shown in Figure 15. 16 participants were involved in the experiments.

5.1.2 Questionnaire (QU)

As part of the experiment involving 16 participants, each participant was required to complete a questionnaire. The questionnaire was scored using the methodology described in references [112], [113], [114]. By analyzing the participant's highest and lowest scores on the five personality traits, their strong personality traits were identified and used to create a comprehensive personality profile for each participant.

5.1.3 Expert Analysis (EA)

To determine each participant's personality, an expert was requested to assess the participant data during human robot interaction and data that stored during interaction. Features were quantified based on their frequency of occurrence, considering it as the most reliable approach by experts. The most frequently observed features were utilized for personality prediction. A total of 16 participants data were analyzed by the expert.

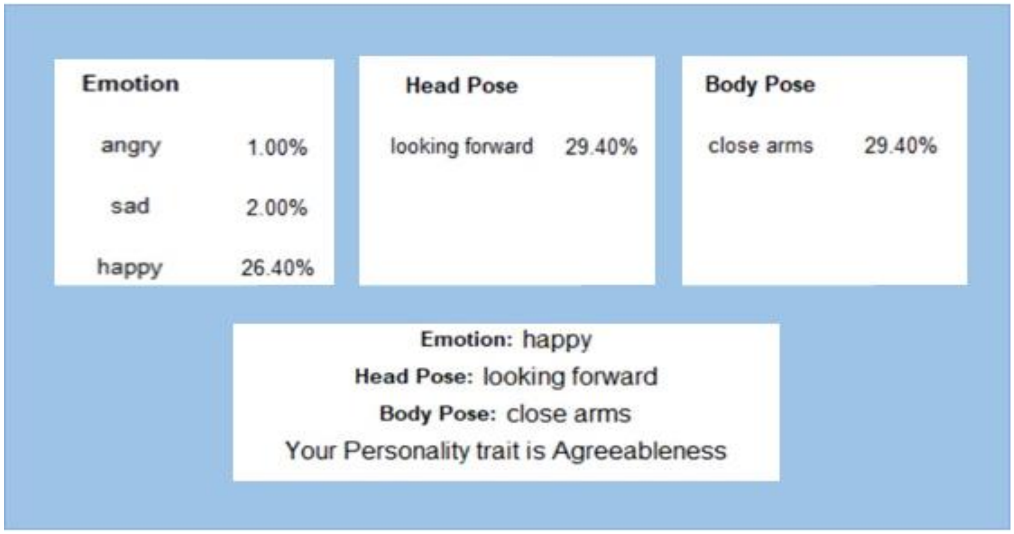

Fig. 15: Graphical User Interface (GUI) for personality prediction using human-robot interaction

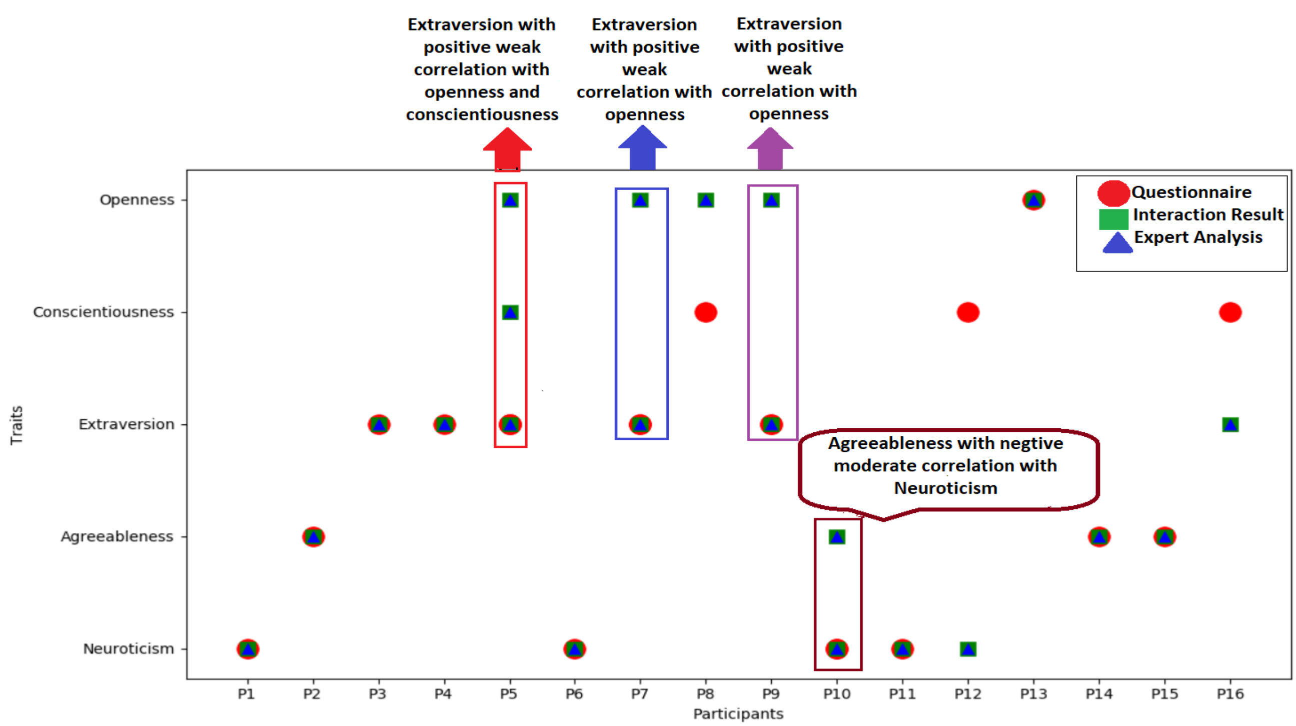

Fig. 16: Result plots of personality profiling system, questionnaire, expert analysis

5.2 Discussion

Understanding personalities is critical using questionnaires. In the questionnaire assessment participant's highest and lowest scores in the five qualities of big five used to characterize single personality profile. Although, single questionnaire assessment result should not be used to draw firm conclusions about a person's personality because personality is multifaceted and multidimensional. Instead, a comprehensive assessment of a person's personality based on a variety of characteristics and aspects should be taken into account [116], [117]. To understand personality nonverbal cues are extracted during human-robot interaction and expert help was taken for confirmation that system is predicting personality correctly. Even though the findings of the questionnaire included some incorrect predictions, the participant's interactions with the robot and expert analysis results were identical.

Participant 5 exhibited extraversion according to the questionnaire, with positive associations to openness and conscientiousness. Participant 7, initially categorized as extraverted, showed a positive linkage to openness through HRI and expert analysis. Participant 8, identified as conscientious in the questionnaire, demonstrated openness in the interaction and expert assessment. However, for participants 12 and 16, the questionnaire's conscientiousness trait corresponded to neuroticism and extraversion, respectively. Participants 9 and 7 had similar outcomes. Participant 10, labeled as neurotic in the questionnaire, was assessed as agreeable with a weak negative association to neuroticism. Extraversion was the most frequent trait, while openness was the least frequent. Conscientiousness did not show significant correlation. Refer to Table 12 and Figure 16 for a visual representation of the results.

Table. 12: Results for Personality Prediction

Participants	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 positive weak correlation with Openness & Conscientiousness	Extraversion with positive weak correlation with Openness & Conscientiousness
P6	Neuroticism	Neuroticism	Neuroticism
P7	Extraversion	Extraversion with positive weak correlation with Openness	Extraversion with positive weak correlation with Openness
P8	Conscientiousness	Openness	Openness
P9	Extraversion	Extraversion with positive weak correlation with Openness	Extraversion with 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

CHAPTER 6

CONCLUSION

In conclusion, this investigation utilized an innovative approach that leveraged Human-Robot Interaction (HRI) to predict personality traits. By combining nonverbal cues, such as facial expressions and body language, with verbal communication, a 44-item Big Five Inventory (BFI) survey, and expert analysis, personality characteristics were successfully predicted based on the Big Five model. The humanoid robot NAO was employed to facilitate an interactive verbal session, during which nonverbal cues were gathered, including facial expressions, head position, and body position. The facial expression module employed the Face Emotion Recognition Plus (FER+) dataset, which had been trained using 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 within the age range of 21-30, with the aim of predicting extraversion, neuroticism, agreeableness, openness, and conscientiousness as personality traits. The results obtained from predicting personality traits through interactions between humans and robots were found to be consistent with assessments made by psychologists. This indicates the potential of using Human-Robot Interaction (HRI) as a means of anticipating personality characteristics based on the Big Five model. The integration of multiple data sources, including survey responses, human-robot interaction, and professional analysis, allowed for a comprehensive approach that enhanced the accuracy of personality prediction. These findings highlight the promise of applying HRI in predicting personality traits and offer insights into the potential applications in various fields. Further research and refinement of this methodology could lead to practical applications in areas such as human-robot interaction, psychology, and personalized user experiences. By continuing to explore and develop this approach, it may be possible to enhance our understanding of human-robot interactions and utilize this knowledge to create more tailored and effective interactions between humans and robots in the future.

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APPENDIX-A-CONSENT FORM

National University of Science and Technology
Islamabad, Pakistan.

RIME Department

Participant Consent Form

Purpose:
The purpose of this study is to analyze human personality. The study is part of the MS thesis, under the supervision of Dr. Sara Ali.
Procedure:
If you agree to be in this study, you will be asked to perform activities as per instructions.
Benefits/Risks to Participant:
There is no personal benefit from your participation in this, but the knowledge received is valuable for research.
Voluntary Nature of the Study/Confidentiality:
Your participation in this study is entirely voluntary, and you may refuse to complete the study at any point during the experiment. You may also stop at any time and ask the researcher any questions you may have.
You will be assigned a number as names will not be recorded. The researchers will save the data file by your number, not by name. Only members of the research group will view collected data in detail. Any files will be stored in a secured location accessed only by authorized researchers.

Contacts and Questions:
At this time, you may ask any questions you may have regarding this study. If you have questions later, you may contact at anum.rime20smme@student.nust.edu.pk , or my faculty supervisor, sarababer@smme.nust.edu.pk.

Statement of Consent:
I have read the above information. I have asked any questions I had regarding the experimental procedure, and they have been answered to my satisfaction. I consent to participate in this study.

Signature of Participants

Anum	Faiq Malik
Amna Imdad.	Abdullah Sheikh
Sana umer	Samreen Ijaz
Usama Jameel	Bilal Umer
Ahmed zahid	Ayesha Usman
Hassan Amjad	Kainat
Waleed	Faiza Imran
Ayesha Baber.	Abdul Hakeem

Thanks for your participation!

APPENDIX-B-44 ITEMS QUESTIONNAIRE

Name : Faiq
How I am in general

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who *likes to spend time with others*? Please write a number next to each statement to indicate the extent to which **you agree or disagree with that statement.**

1 Disagree Strongly	2 Disagree a little	3 Neither agree nor disagree	4 Agree a little	5 Agree strongly

I am someone who…

1. 4 Is talkative
2. __2___ Tends to find fault with others
3. 4 Does a thorough job
4. _2____ Is depressed, blue
5. 4 Is original, comes up with new ideas
6. _5____ Is reserved
7. __5___ Is helpful and unselfish with others
8. _3____ Can be somewhat careless
9. _4____ Is relaxed, handles stress well.
10. _4____ Is curious about many different things
11. _4____ Is full of energy
12. _1____ Starts quarrels with others
13. _4____ Is a reliable worker
14. _3____ Can be tense
15. __4___ Is ingenious, a deep thinker
16. __4___ Generates a lot of enthusiasm
17. _4____ Has a forgiving nature
18. __1___ Tends to be disorganized
19. __1___ Worries a lot
20. __4___ Has an active imagination
21. __4___ Tends to be quiet
22. __4___ Is generally trusting
23. 4 Tends to be lazy
24. ___5__ Is emotionally stable, not easily upset
25. 4 Is inventive
26. __4___ Has an assertive personality
27. 2 Can be cold and aloof
28. _5____ Perseveres until the task is finished
29. __2___ Can be moody
30. ___4__ Values artistic, aesthetic experiences
31. __2__ Is sometimes shy, inhibited
32. __4___ Is considerate and kind to almost everyone
33. __4___ Does things efficiently
34. __4___ Remains calm in tense situations
35. __5___ Prefers work that is routine
36. _4____ Is outgoing, sociable
37. _2____ Is sometimes rude to others
38. ___5__ Makes plans and follows through with them
39. ___1__ Gets nervous easily
40. ___4__ Likes to reflect, play with ideas
41. ___4__ Has few artistic interests
42. ___5__ Likes to cooperate with others
43. __1___ Is easily distracted
44. ___2__ Is sophisticated in art, music, or literature

APPENDIX-C- 44-ITEM QUESTIONNAIRE SCORING

Big Five Model Scoring

(R denotes Reverse Scoring)

(1=5) (2=4) (3=3) (4=2) (5=1)

Extraversion:

1___4_ + 6R_1__ + 11__4__ + 16___4__ + 21R__2___ + 26___4___ + 31R__4___ + 36__4____ = Total __27_____

Total Score ____27__ / 8 = 3.37

Agreeableness:

2R__4_ + 7 ____5__ + 12R__5____ + 17___4____ + 22__4_____ + 27R___4_____ + 32___4____ + 37R__4____ + 42___5____ = Total ___39_____

Total Score ____39_ / 9 = **4.33**

Conscientiousness:

3____4__ + 8R__3_____ + 13__4_____ + 18R___5_______ + 23R___2______ + 28__5_______ + 33___4_____ + 38___5___ + 43R___5______ = Total __37_______

Total Score __________37__ / 9 = 4.11

Neuroticism:

4______2_____ + 9R___2______ + 14___3_____ + 19___1_____ + 24R____1______ + 29_____2___ + 34R______2___ + 39___1____ = Total ______14_____

Total Score _______14_____ / 8 = 1.75

Openness:

5____4_____ + 10____4______ + 15____4_____ + 20______4___ + 25____4_____ + 30______4______ + 35R___1_____ + 40_____4____ + 41R____2____ + 44_______2____ = Total ___33______

Total Score ______33______ / 10 = 3.3

APPENDIX-D-EXPERT REPORT

Report After Analysis of Features Labeling and Data

As a career counselor, I have sound knowledge of career guidance and counseling. I am also able to practice counseling sessions with clients for their career development process. Moreover, as a career counselor, I understand the processes involved in administration and interpretation of different careers related tests, such as personality, interest, and aptitude tests etc.

I had received a 'features labeling' document, which contained sequences of three human body features (Emotion, Head Orientation and Body Pose) against each of the five personality traits i.e., Extraversion, Agreeableness, Neuroticism, Openness and Conscientiousness. And I find the labeling of the human body features accurate, as per my knowledge and understanding.

During the experiment 16 participants were present. For analyzing the personality of each participant there nonverbal cues i.e., Emotion, Head Orientation and Body Pose was observed during the human-robot interaction. And based on the observed data I have analyzed that each participant has the following traits given in table.

Participants	Traits
P1	Neuroticism
P2	Agreeableness
P3	Extraversion
P4	Extraversion
P5	Extraversion with positive weak correlation with Openness & Conscientiousness
P6	Neuroticism
P7	Extraversion with positive weak correlation with Openness
P8	Openness
P9	Extraversion with positive weak correlation with Openness
P10	Agreeableness with negative moderate correlation with Neuroticism
P11	Neuroticism
P12	Neuroticism
P13	Openness
P14	Agreeableness
P15	Agreeableness
P16	Extraversion

Name: Tahira Zakir (Certified Career Counselor)

MS- Career Counseling & Education

Dep: Department of Behavioral Sciences

School: School of Social Sciences and Humanities