Comparison of Quantitative Proxemics to measure trust in HRI

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MS Robotics and Intelligent Machine Engineering

Thesis Supervisor:

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Declaration

I certify that this research work titled "*Comparison of quantitative proxemics to measure trust in HRI*" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged/referred.

Signature of Student

Fatima Ahmad

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Copyright Statement

Acknowledgment

I express my gratitude to ALLAH for His blessings and guidance in completing my thesis successfully. Without Allah's help and guidance, I would not have been able to accomplish anything. I acknowledge that anyone who assisted me during my thesis journey, whether it be my parents or others, was through Allah's will, and therefore, all praise belongs to Him alone. Next, I want to give special thanks to my supervisor, Dr. Sara Ali, who provided me with a valuable opportunity to accomplish this great task and for her unwavering support throughout. I would also like to extend my appreciation and gratitude to Dr. Yasar Ayaz and Dr. Khawaja Fahad Iqbal, who served on my thesis guidance and evaluation committee and offered their assistance and cooperation. Lastly, I am grateful to my parents and all those who have helped, contributed, and support me during my education.

Dedicated to my beloved parents and siblings whose tremendous support and cooperation led me to achieve this wonderful milestone

Abstract

With the increase in the affordability of robots and development in the robotics field, humans have to work in collaboration with robots in many domestic and industrial tasks. With these advancements in the robotics field, it is required to address the challenge of creating a trustworthy environment. However, while working with robots, it is necessary to maintain some distance from the robot to ensure the safety and comfort of a human. To address this problem, we proposed a virtual reality (VR) based human-robot interaction (HRI) task where we can practice interaction between humans and humanoid robots to analyze the trust of humans in robots in terms of social interaction parameters such as the distance of the robot from the human while moving towards the human. In our research, we show a novel idea to measure the trust of human in a robot through EEG signals and then compare it with the real-world HRI task. The comfortable distance while interacting with the robot is determined through Brain Computer Interface (BCI). Along with the use of survey-based assessment of the subject, a standard, and more efficient BCI system is also used to record the users' brain activity in different HRI zones for the study of human emotional state in these zones. Real-time data is required to analyze the effect of social parameters such as the speed of the robot and the comfortable distance on human mental state and this is done by collecting the electroencephalography (EEG) signals of the participants while they are performing the HRI tasks in both VR and real world. The questionnaire is used to compare the results of the BCI for each subject. Experimental results showed that the level of closeness between the robot and the human can affect the way that the human perceives and interacts with the robot. According to the BCI results most of the participants felt comfortable when the robot enters their personal zone with 28% relaxation and 26% stress level as compared to when the robot entered their intimate zone and the stress level increased to 32% and relaxation decreased to 25%. Participants trust virtual robots more than real robots as they are more comfortable in VR interaction as compared to interacting with real robots. BCI results proved that training in the VR framework improves the real-world HRI experience. This study provides valuable insights into the human's cognitive and emotional response to different HRI zones and highlights the importance of considering social parameters, such as proximity, in the design and development of robots for humans.

Keywords: Brain-Computer Interface; Human-Robot Interaction; Virtual Reality; HRI zones; proxemics

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CHAPTER 1: INTRODUCTION

Advancements in the robotics field and increases in the use of robots in both industrial and domestic areas allow humans to collaborate and work with robots (Sheridan, 2016). Human-Robot Interaction (HRI) refers to the study of the interactions between humans and robots. It is a multidisciplinary field that combines aspects of robotics, psychology, engineering, and human-computer interaction. HRI research aims to design and develop robots that can interact with humans in natural, intuitive, and effective ways (Villani et al., 2018). The increase in the use of robots has resulted from advancements in manufacturing systems, computing powers, communication systems, and information systems, which are reflected in the idea of Industry 4.0 (Lasi et al., 2014).

When humans and robots cooperate to perform a certain task, this is referred to as human-robot work collaboration (HRWC) (You et al., 2018). Through this partnership, people can delegate tiresome and repetitive work to their robots (Sauppé & Mutlu, 2014). Additionally, the usage of robots frees people to concentrate on other jobs that are difficult for robots to complete (Tan et al., 2009)Humans often feel unsafe while working with robots, which poses a significant obstacle to using human-robot interaction (Bartneck et al., 2009). Regardless of the level of safety, humans are less eager to work with or alongside robots when they feel it is risky to do so (Atkinson & Clark, 2014)The degree to which someone perceives that it is safe to engage in a behavior known as perceived safety.

As the demand for robots increases in all areas, research and development in the field of robotics also increased in the last decades. The purpose and the target have been always to provide a simple, trustworthy, reliable, and easy-to-use interface between humans and robots (De et al., 2019). To assure the above-mentioned objectives there are more challenges during the collaborative tasks, Hancock et al. (Hancock et al., 2011) give us a study of creating trustworthy interaction between humans and robots. (Sanders et al., 2011)The study presented that humans could gain or lose trust by having certain abilities such as pre-training with the robots, social factors like distance from the robot and the speed of the robot is the dominant factor of human trust in robots. Our research finds out how the distance from the robot affects the trust of humans in robots in terms of safety and how pre-training in a virtual reality (VR) platform improves the trust in robots.

Previous research has shown that the robot's proxemics behavior significantly affects the level of acceptability and is greatly influenced by subjective and demographic variables. The study of spatial distances employed in contact is known as proxemics. For instance, (Vithanawasam & Madhusanka, 2018) revealed that participants stood too close to the robot in 40% of the scenarios that were studied, indicating that they did not consider the robot as a social actor. Also(Huettenrauch et al., 2006), individuals communicate with robots at a distance that is similar to the personal zone that people use when speaking to friends, indicating that they did not treat the robot as a person. This research provides a detailed study of HRI zones and relates these zones with human comfort with robots.

Our main goal is to measure human trust in robots through EEG signals by analyzing human mental states (level of stress and level of relaxation) during HRI. We analyzed the human mental state using BCI in different HRI zones, by changing the distances between the human and the robot during the HRI task. Real-time data is acquired to analyze the impact of social parameters, specifically the comfortable distance, on the human mental state during human-robot interaction (HRI). The method used to collect this data is by measuring the electroencephalography (EEG) signals of the participants while they perform HRI tasks.

Additionally, a questionnaire is used to compare the Brain-Computer Interface (BCI) results for each subject. The experimental results reveal that the level of closeness between the robot and the human can have an impact on how the human perceives and interacts with the robot. This research highlights the importance of considering social parameters in the design and development of robots that interact with humans, as they can significantly affect the user experience and effectiveness of the interaction. These results indicate that the proximity of the robot to the human has a significant impact on the participant's mental state during HRI. The use of BCI in this study also demonstrates the potential of advanced technologies for in-depth studies of human mental states during HRI. Overall, the study provides valuable insights into the factors that influence people's trust in robots during HRI, such as proximity and familiarity, and suggests that VR training can effectively improve trust in robots. These findings could have practical implications for the design and implementation of robots in various settings, such as healthcare, education, and entertainment.

CHAPTER 2: LITERATURE REVIEW

2.1. Human trust in robots

Human trust in robots refers to the belief and confidence that individuals have in the reliability, competence, and intentions of robots (Billings et al., n.d.). It is a multidimensional concept that encompasses various aspects of trust, including cognitive, affective, and behavioral components(Herse et al., 2023). In the era of industrialization and automation, the development of new systems which is meant to collaborate closely with humans posed a significant challenge in ensuring safety(Tsarouchi et al., 2016) . Several factors contribute to the development of trust in robots. These factors include the robot's reliability, predictability, transparency, consistency, and perceived intentionality(Sheridan, 2016). These systems include personal and professional service robots (Lambert et al., 2020), designed to operate in diverse environments while interacting and cooperating with humans (Ali et al., 2023). The broader field of human-robot interaction recognized the critical role of human safety in fostering a harmonious coexistence between humans and robots (Villani et al., 2018).

In the realm of HRI, the captivating and pivotal area of research revolved around human trust in robots (Kok & Soh, 2020). It became apparent that robots risked being underutilized or misused if they lacked the trust of their human counterparts (Herse et al., 2023). Thus, trust emerged as a crucial factor that enabled robots to transcend their industrial applications and enter the domain of human social environments. Previous studies have employed questionnaires and behavioral measures to measure trust in robots (Yu et al., 2014).

2.2. Relating quantitative proxemics with trust in robots

In the context of proxemics, personality traits play a role in how public spaces are utilized and the perception of socially acceptable movements. Consequently, robots should be capable of adapting their behavior based on the individual they are interacting with (Walters et al., 2018). People respond and behave differently depending on their spatial needs, emphasizing the importance of robots (mobile, social, humanoids, and mechanoid etc.) effectively utilizing the space(Petrak et al., 2019), (Camara & Fox, 2022). Moreover, a person's current position and activity can impact their comfort level in interacting with a robot (Walters et al., 2018). As per a research study, modifying robot behavior significantly influences user acceptance and perceptions of safety (Rossi et al., 2017). This study conducted a pilot investigation to assess the comfortable distance between humans and robots, considering the participants' attitudes and personalities (Yu et al., 2014). (Camara & Fox, 2021). The ultimate goal of this research is to unify the fields of proxemics and trust in HRI and provide quantifiable models that can be applied in real-world operational HRI . The comfortable distance was determined using EEG signals to measure human comfort levels and compared with questionnaire responses.

2.3. Human-robot interaction and Virtual Reality (VR)

The growing popularity of Virtual Reality (VR) in Human-Robot Interaction (HRI) research can be attributed to its immersive experiences, interactive nature, and embodiment capabilities. VR provides researchers with the ability to quickly iterate on robot designs and behaviors at a lower cost and effort compared to real-world experiments (Sagnier et al., 2020). Unlike other methods such as simulations or video-based experiments, VR offers a unique sense of presence (L. Liu et al., 2023). A study presented by Liu et al. (L. Liu et al., 2023) demonstrated that collaborative task performance with a virtual robot was significantly better in VR simulations compared to 2D robotic simulations. Another study found that using VR for teleoperation tasks led to higher usability and lower workloads compared to traditional joystick or keyboard control with a computer monitor (Whitney et al., n.d.). Previous research conducted by (Pérez et al., 2019), (Matsas & Vosniakos, 2017), (Magnenat &Thalmann et al., 2020) has suggested that VR platforms can be utilized for training in human-robot interaction. These findings highlight the potential of VR platforms to address HRI-related issues. In our research, we utilized a VR platform effectively for studying proxemics and pre-training to observe its impact on enhancing trust in robots.

2.4. A Comparative Exploration of HRI in Virtual Reality vs. the Real World

The main objective of research on human-robot interaction in real-world settings is to understand the mechanisms of social and physical interaction and use that understanding to design robots that can interact more effectively with humans (Kok & Soh, 2020). Researchers have proposed various methods to achieve this goal such as analyzing human interaction behavior with humanoid, mobile, and pet robots under different social and physical conditions (L. Liu et al., 2023), (Sagnier et al., 2020). However, conducting HRI experiments in real-world settings presents several challenges, including limited opportunities to set up interaction fields and the high cost of large-scale experiments, particularly when the aim is to teach robots through demonstration or instruction (Lambert et al., 2020). (Arents et al., 2021)This research hypothesizes that VR environments can provide unique advantages for studying HRI, including increased control over experimental conditions, the ability to simulate diverse scenarios, and the potential for immersive and realistic interactions. This paper focuses on investigating these disparities, particularly in terms of proxemic preferences, while also exploring the impact of visual familiarity and spatial sound in the VR experience (Rui Li et al., 2019), (Brannon Barhorst et al., 2021), (Feng et al., 2020). The findings will contribute to a deeper understanding of the benefits and limitations of VR as a tool for studying and improving HRI.

2.5. Quantifying Human Cognitive States

Emotion recognition techniques such as facial recognition (El Ayadi et al., 2011), speech analysis (Fernández-Caballero et al., 2016), and body language (Vithanawasam & Madhusanka, 2018) have limitations due to cultural differences and potential alterations. In contrast, electrocardiography (ECG) and electroencephalography (EEG) are considered more reliable methods for measuring the emotional states of any human. Electroencephalography (EEG) is a non-invasive technique that measures the bioelectrical activity of the brain using electrodes placed on the scalp (Edla et al., 2018). EEG signals are becoming more important as a psychophysical marker for measuring stressful mental states, particularly in the context of brain-computer interface and online assessments of mental stress, mental workload, and mental fatigue (Reuderink et al., 2013), (Yurci & Ramirez, n.d.). One of the main reasons to prioritize EEG signals for emotion recognition is that it gives results that are more realistic as the brain activity is the internal signal and it is harder to influence it voluntarily (Shu et al., 2018). EEG captures electrical impulses as brainwaves, characterized by their frequency and amplitude (Zhang et al., 2010). Low-frequency waves, such as delta and theta, are associated with relaxation and sleep, while higher-frequency waves, such as alpha, beta, and gamma, are produced when a person is awake, attentive, or responding to their environment (Blinowska & Durka, n.d.), (Zainuddin et al., 2014). The alpha waves relate to the relaxed state of the individual while the beta rhythm is related to an alert or stressed condition (Y. Liu & Sourina, 2012). BCI systems interpret these brain signals into commands or actions, enabling a wide range of applications in measuring human mental states during tasks like Human-Robot Interaction (HRI) (Shu et al., 2018).

Brain-Computer Interface (BCI) systems in HRI have potential advantages, including validating the effectiveness of adaptive multi-robot therapy for children with ASD (Ali et al., 2019). Cognitive states are analyzed using EEG neuroheadsets before and after the intervention. The research aims to raise awareness in the HRI community(Alimardani & Hiraki, 2020)Additionally, social engagement components from the human partner's brain, such as the intention to initiate eye contact and distinguishing between initiator and responder in gaze contact, are recorded with EEG (Stefan Ehrlichet al., 2014), (Jang et al., n.d.).

2.6. Contribution

We propose a Virtual Reality (VR) framework to investigate the impact of quantitative proxemics on trust in robots during human-robot interaction. Our research aims to analyze the influence of proximity on human trust in robots, particularly in terms of safety and explores how pre-training in a VR platform can enhance trust. Using an EEG-based Brain-Computer Interface (BCI) neuroheadset, we measured participants' real-time EEG data during HRI tasks to examine their mental states. The experimental results revealed that the proximity of the robot significantly affected how participants perceived and interacted based on their stress and relaxation levels. These findings highlight the importance of considering social parameters, such as proximity and familiarity, in robot design to improve user experience and interaction effectiveness. Moreover, the study demonstrates the potential of VR training in enhancing trust in robots.

CHAPTER 3: ARCHITECTURE

To create a trustworthy environment in human-robot interactions, it is important to consider the effects of proxemics on human related to trust in robots. When it comes to replacing robots platforms with virtual platforms, it is crucial to determine whether training in VR is equivalent to real-world training and whether it enhances trust in real robots. Based on literature presented in this paper, this study presents two hypothesis:

H_1: Proximity and familiarity are the factors that influence trust in robots during human-robot interaction.

H_2: It is hypothesized that training in VR can enhance real-world HRI interactions and subsequently improve trust in real robots.

For this purpose, trust in robots is measured using brain-computer interfaces system, which provide a set of mental state values from which stress and relaxation levels can be extracted during an interaction

3.1. Mathematical modelling

H_1 states that proximity and familiarity are influential factors in determining trust during Human-Robot Interaction (HRI). This study specifically focuses on the personal and intimate zones as defined by (Hall et al. 1986). By analyzing the influence of distance on participants' perceptions and trust in robots, we can gain insights into the role of proxemics in trust formation. According to eq. 1, trust in real (T_{real}) and virtual ($T_{virtual}$) robots is a function of human-robot proxemics (Prox) and familiarity (Fim). Where, proximity refers to the HRI zones that are personal zone (0.15-0.45m) and intimate zone (0.45-1.2m) illustrate in eq. 2. Familiarity, on the other hand, represented by binary values, where 0 indicates non-familiar participants and 1 represents familiar participants.

Trust in robots (T_{robot}) can be quantitatively evaluated using Brain-Computer Interfaces ($BCI_{results}$) indicate in eq. 3. BCI allow for the measurement and extraction of mental state values, such as stress and relaxation levels, which are represented as real numbers. Eq. 4 illustrate the relationship between trust in robots and these mental state metrics. Trust is directly proportional to relaxation and inversely proportional to stress. These equations provide a mathematical framework for understanding the connection between mental states and trust in robot.

$$f(Trust) = \begin{cases} T_{real}, & \in (Fim, Prox) \\ T_{virtual}, & \in (Prox, Prox) \end{cases} \quad (1)$$

$$f(Fim, Prox\ ) = \begin{cases} Fimilarity, & \in (0,1) \\ Proxemics, & \in (0.15m < x_p < 0.45m), (0.45m < x_i < 1.2m) \end{cases} \quad (2)$$

$$T_{robot\ \in}\ BCI_{results} \quad (3)$$

$$BCI_{results} = \begin{cases} Stress\ (S) \\ Relaxation\ (R) \end{cases} \in \mathbb{R}, \quad \text{where } \{T_{robot}\ \alpha\ R \cap T_{robot}\ \alpha\ 1 \backslash S\} \quad (4)$$

Previous research conducted by (Pérez et al., 2019), (Matsas & Vosniakos, 2017) have suggested that VR platforms can be effectively employed for training in human-robot interaction. Building upon this premise, hypothesis H_2 posits that training in VR can enhance real-world human-robot interaction and foster greater trust in actual robots. According to eq. 5 trust in robots within the virtual environment ($T_{virtual}$) exceeds the initial trust in the real world prior to VR interaction $(T_{real})_b$. Furthermore, as trust in real robots improves following VR interaction $(T_{real})_a$, it surpasses both the trust in the virtual environment and the trust in the real world prior to VR interaction.

$$(T_{real})_b < T_{virtual} < (T_{real})_a \quad (5)$$

$$(T_{real})_{b,a} \cap T_{virtual} \in BCI_{results} \quad (6)$$

3.2. Human-Robot Interaction in Real World

PyCharm is a popular integrated development environment (IDE) for Python programming. PyCharm provides a range of features such as code completion, debugging, code analysis, version control integration, and more, which can help developers be more productive and efficient in their Python development work. The Emotiv API is a software development kit (SDK) that allows developers to create applications that interact with Emotiv's brain-computer interface (BCI) devices. The Emotiv API provides a set of tools and libraries that enable developers to build applications that can read, process, and interpret brain signals captured by Emotiv's headsets. Two tasks are developed in PyCharm according to the user’s choice the task is selected. Emotive API provides the human mental state matrices into the software in real-time. These matrices provide the values of stress and relaxation.

Figure 3.1 shows the architecture of this study. Humans wearing the headset interact with the Nao robot. The first component in the architecture is the real-time EEG data-stream adapter that captures the bioelectric activity of the brain during the task and converts them into signals of different frequencies. These signals are then converted into human emotions such as stress, relaxation, focus, engagement, interest, and excitement. For the Emotive Insight 2.0 headset, the software used as an adapter is Emotive Pro, which provides the needed set of emotions. When it comes to human trust in robots, the level of comfort and relaxation experienced by humans during interactions plays a crucial role. If a human feels at ease and experiences minimal stress while interacting with a robot, it generally indicates a higher level of comfort and, subsequently, a greater level of trust. The stress and relaxation levels of humans are measured by collecting EEG signals and processing them and through human mental state matrices provided by the Emotiv software. Therefore, arrow 1 in Figure 3.1 shows that the Emotiv Insight 2.0 EEG headset is connected to the Emotiv software through Bluetooth. After adjusting the headset onto the participant correctly, electrode connectivity was checked, which should be above 90% for obtaining good results. Raw EEG data is recorded and exported from the software in the form of .csv files for offline processing of the signals and the live stream of mental state metrics is stored during the experiment. In the schematic diagram of the architecture arrow 2 indicate the second component, which is a PyCharm software used as a robot adapter where there are two tasks programmed for the Nao robot. Task 1 is to enter the robot into the personal zone of the participant and task 2 is the robot enter the intimate zone of the participant. There is a verbal interaction by the robot at the end of both tasks and the value of mental state that is stress and relaxation level is noted down during these tasks. Arrow 3 shows the offline processing of the Raw EEG data recorded during these tasks to support the results obtained through mental state metrics. Figure 3.2 shows the pseudocode for the tasks of human-robot interaction and data acquisition in the real world.

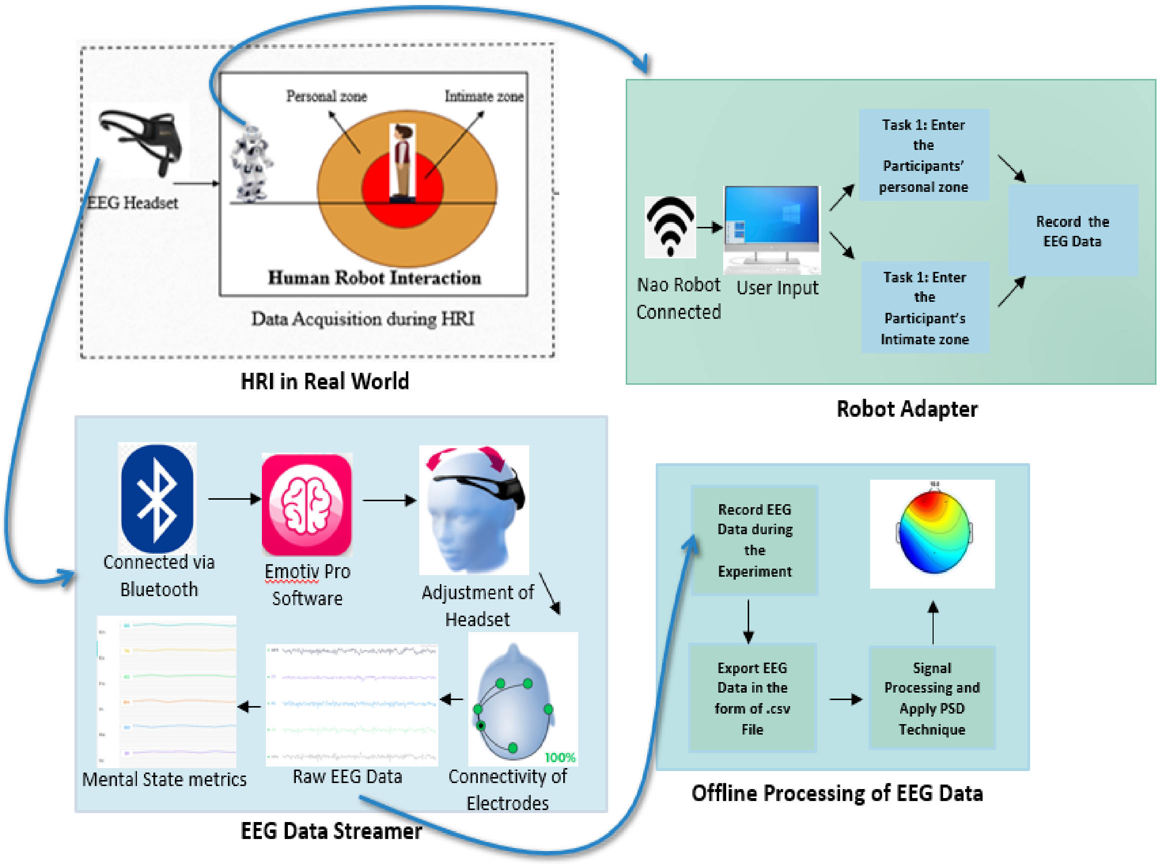

Figure 3.1: Architecture for human-robot interaction in Real World

```
Inialization
\\performance matrices
mental state metrics: ['engagement', 'excitment', 'focus', 'interest', 'realaxation','stress']
headset_id =  ' Enter headset id '
Nao IP adress = ' Enter IP adress'
Stress = 0
Relaxation = 0

Data_Acquisition( )
IF headset_is_connected
            GET mental-state_matrics( )
            stress=performance_matrices[value_of_stress]
            relaxation=performance_matrices[value_of_relaxation]
ELSE get_permission
            connect_to_headset
END
```

```
NaoRobot_walk( )

\\Move_Forward
Move_Forward(X_1, Y_1, Theta_1,Frequency_1)

\\Stop_Walking
X_2 = 0.0
Y_2= 0.0
Theta_2= 0.0
Frequency_2 = 0.0

Task_Selection = {task1,task2}
Task_Selection = (USER_INPUT)

IF task1
        Move_Forward(X_1 = 1.4m, Y_1= 0.0, Theta_1= 0.0, Frequency_1 = 1.0)

ELSE
        Move_Forward(X_1 = 1.7m, Y_1= 0.0, Theta_1= 0.0, Frequency_1 = 1.0)
        Stop_Walking
END
```

Figure 3.2: Pseudocode for the tasks of human-robot interaction and data acquisition in real world

3.3. Human-Robot Interaction in Virtual Reality

To conduct the study on VR-based human-robot interaction, the VR platform was designed in the Webots robot simulator and Oculus Quest 2 VR headset was used to immerse in the VR environment. Webots are widely used simulators in the robotics community and have active development communities and support forums. Webots support multiple robot models, including the Nao robot by Softbank Robotics, and also support Oculus Quest 2 virtual reality headset. Webots built-in VR editor is used to create a virtual reality environment and the Nao robot from the official website of Softbank Robotics is imported into the VR environment. As Webots provides support for Choreographe, which is a graphical programming tool developed by Softbank Robotics for programming Nao and other Softbank Robotics robots. Choreographe was used to program the Nao robot and then export the Choreographe project as a Python script. This Python script was then imported into the Webots to control the Nao robot's movements and behaviors during the simulation. Figure 3.4 and Figure 3.5 shows the VR framework developed for the HRI tasks in a virtual environment.

Figure 3.3 shows the architecture of the HRI study conducted in virtual reality. To perform the human-robot interaction in VR participant has to wear both the VR headset and the EEG headset. Arrow 1 in Figure 3.3 Shows the connectivity and working of the EEG headset and arrow 2 indicate that the Oculus Quest 2 VR headset is connected to the PC through an Oculus link cable. Oculus software is used for setting up the VR headset. Once the setup is complete quest 2 is ready for the VR experience. VR framework is designed in the Webots and VR headset is accessed in it to conduct the human-robot interaction in Webots virtual environment.

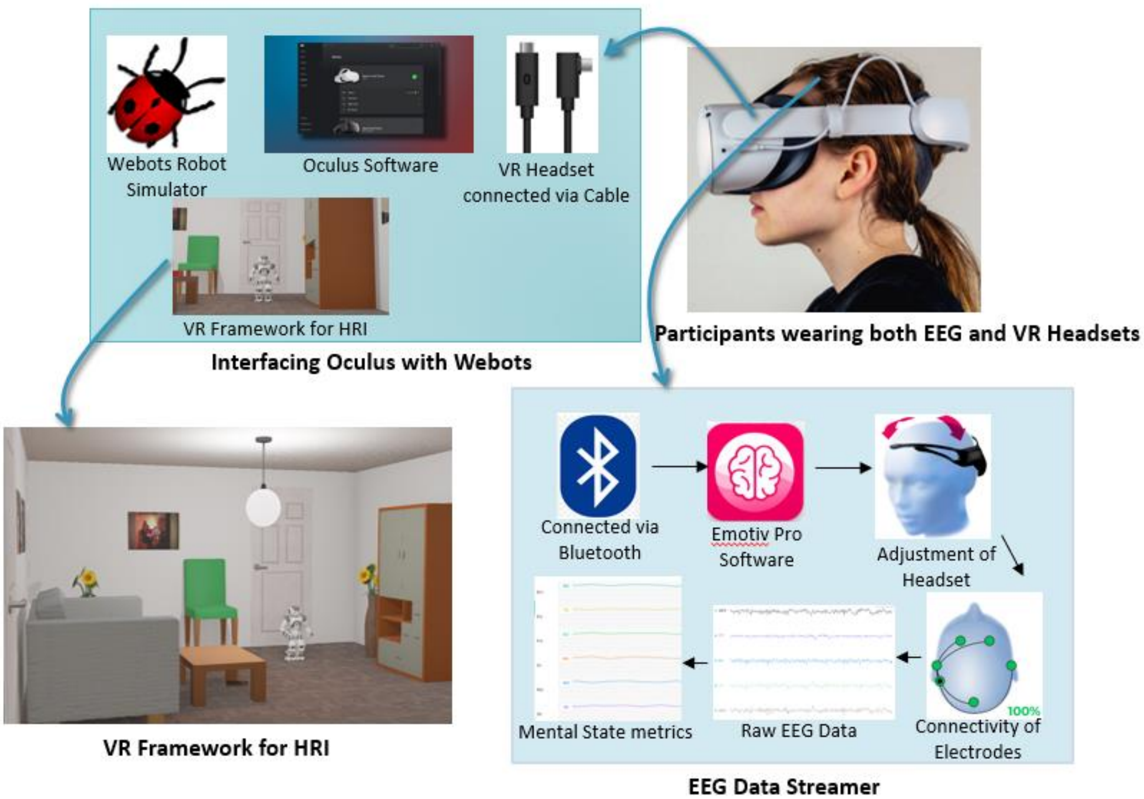

Figure 3.3: Architecture for human-robot interaction in Virtual Reality

Figure 3.4: Virtual Reality platform for investigating HRI. The virtual robot in the framework is similar in appearance and capabilities to the Nao robot by Softbank Robotics

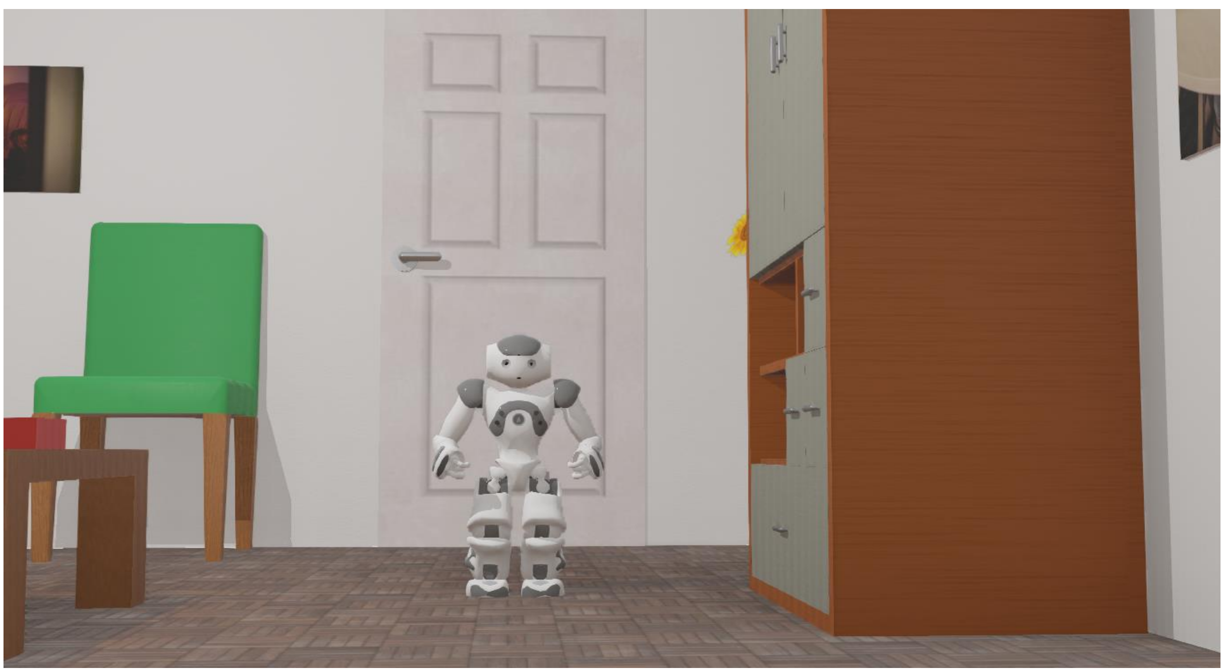

Figure 3.5: Participants view the Nao robot walk towards them from the front

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CHAPTER 4: METHODOLOGY

4.1. Participants

Nine healthy participants with an average age of 30 ± 6 years took part in this study out of which seven are males and two are females. Out of nine participants, four are familiar with the robot and the other five are those who interact with the robot for the first time. Since participants were chosen as volunteers, they were not compensated and before starting the experiment, they were asked to sign the informed consent form. Figure 4.5 shows the scanned copy of the consent form signed by the participants. The experiment took place in a closed and silent room to avoid atmosphere noise. Labels were placed on the ground for the starting position of the robot, for the sitting position of the robot, and for the starting of the personal and intimate zone. The participants were asked to wear the EEG headset and sit on the ground comfortably at a predefined position from the robot that is 2m facing towards the Nao robot. Figure 4.1 shows the experimental setup for the HRI task.

4.2. Experimental Setup and Implementation

Following are the two tasks for the human-robot interaction.

- The robot approaches the participant from the front and stops at a distance of 0.6m away from the subject, which means that the robot enters its personal zone. Speed is kept constant for both tasks.
- Now the robot approaches the participant from the front and stops at a distance of 0.3m away from the subject, which is the intimate zone in HRI.

Figure 4.1: Experimental Setup for Human-Robot Interaction in Real World

Figure 4.2 shows all the steps followed by the participants for the whole experiment. At the start of the experiment, participants have to sign the informed consent form. To conduct the human-robot interaction in the real world the participants were asked to wear the EEG headset and sit on the ground comfortably at a predefined position from the robot that is 2m facing towards the Nao robot. Figure 4.1 shows the experimental setup for the HRI task in the real world. After completing the real-world experiment participant fill the Questionnaire 1, Figure 4.3 shows the scanned copy of Questionnaire 1 filled out by the participant. Questionnaire 1 covers almost all the questions related to the trust of humans in the robot in different HRI zones in the real world. Participants would have to answer all five questions by mark on one option from two (Yes or No). Now they were asked to sit in front of the PC and wear both the VR and EEG headsets for the VR human-robot interaction. After the VR experience real-world human-robot interaction was performed again to measure the improvement in trust in robots after VR experience. At the end of the experiment, the participants were asked to fill out the questionnaire 2, form that would tell the perception of the human during the HRI in both VR and real world. Figure 4.4 shows the scanned copy of questionnaire 2 that is about comparing the interaction between real and virtual robots and about pre-training in VR improves trust in robots or not. Both tasks are performed two times on each subject. In every trial, the human mental state of the human in the form of a set of emotions is stored and analyzed. The experiment that involves all tasks took ~45 min.

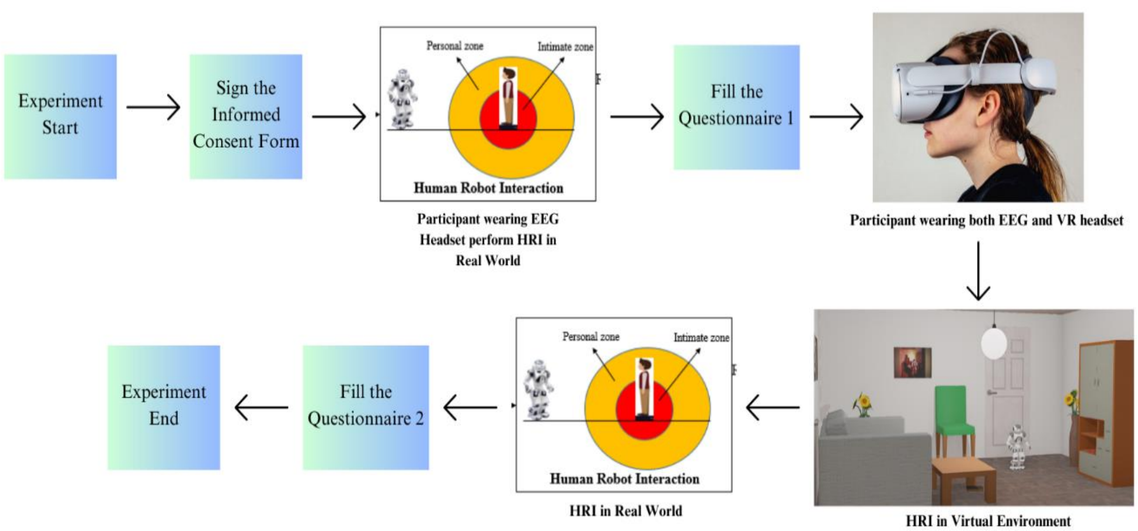
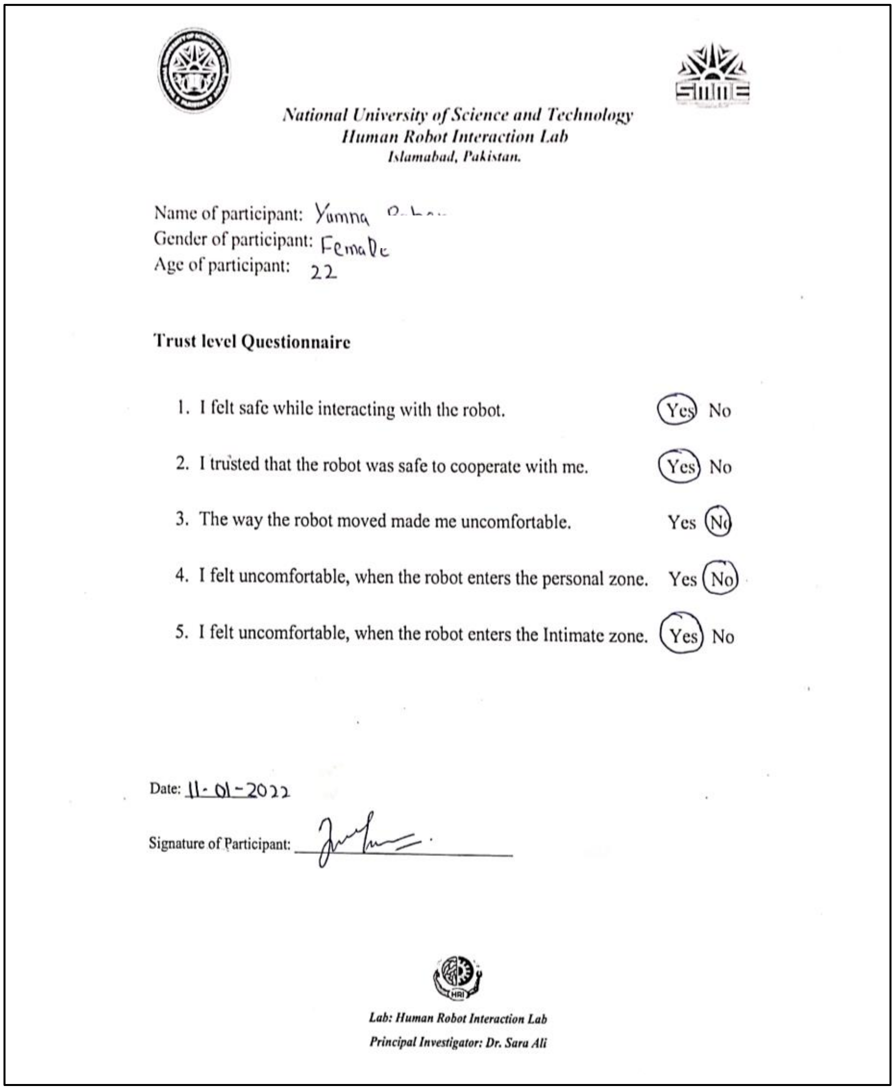


Figure 4.2: Flow chart describe the sequence that is followed during the experiment



National University of Science and Technology
Human Robot Interaction Lab
Islamabad, Pakistan.

Name of participant: Yumna
Gender of participant: Female
Age of participant: 22

Trust level Questionnaire

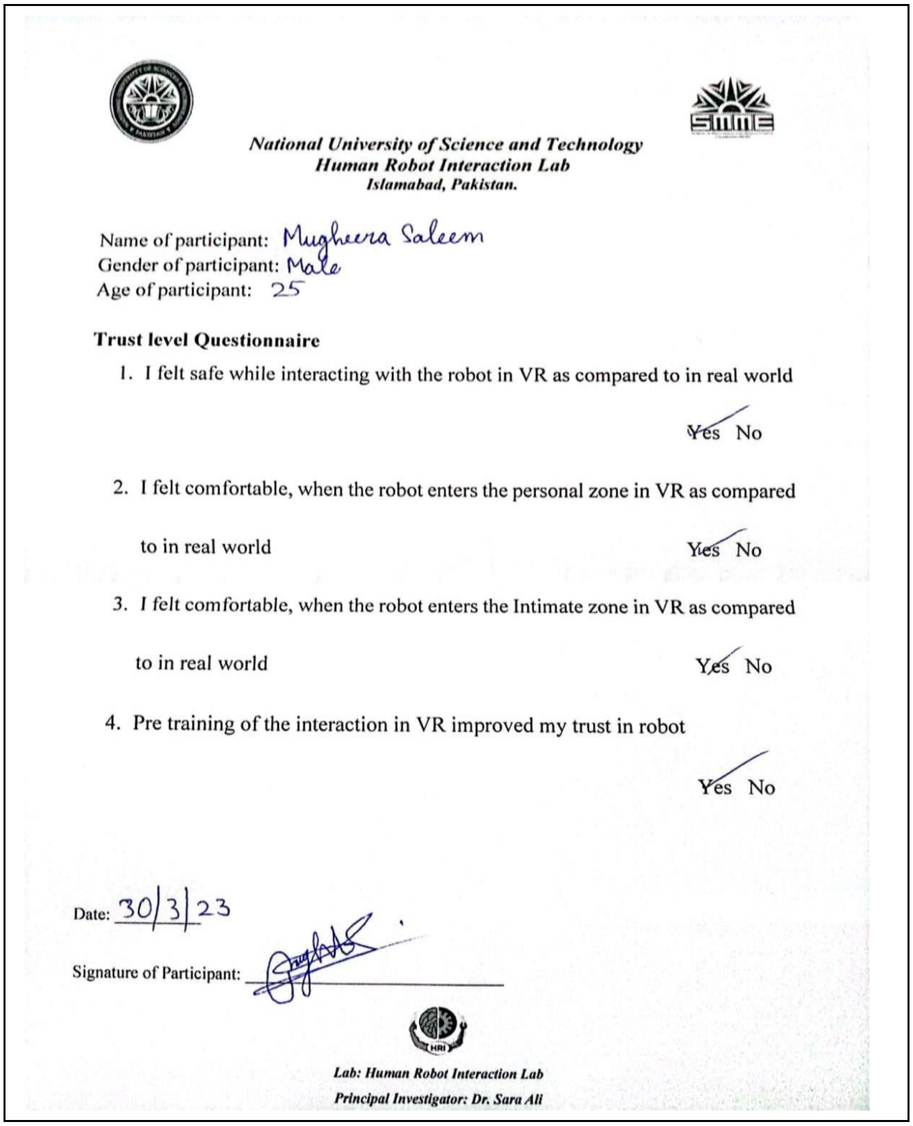
1. I felt safe while interacting with the robot. Yes No
2. I trusted that the robot was safe to cooperate with me. Yes No
3. The way the robot moved made me uncomfortable. Yes No
4. I felt uncomfortable, when the robot enters the personal zone. Yes No
5. I felt uncomfortable, when the robot enters the Intimate zone. Yes No

Date: 11-01-2022

Signature of Participant: ______

Lab: Human Robot Interaction Lab
Principal Investigator: Dr. Sara Ali

Figure 4.3: Questionnaire 1 form filled out by the participants


National University of Science and Technology
Human Robot Interaction Lab
Islamabad, Pakistan.

Name of participant: Mugheera Saleem
Gender of participant: Male
Age of participant: 25

Trust level Questionnaire

1. I felt safe while interacting with the robot in VR as compared to in real world

   Yes No

2. I felt comfortable, when the robot enters the personal zone in VR as compared to in real world

   Yes No

3. I felt comfortable, when the robot enters the Intimate zone in VR as compared to in real world

   Yes No

4. Pre training of the interaction in VR improved my trust in robot

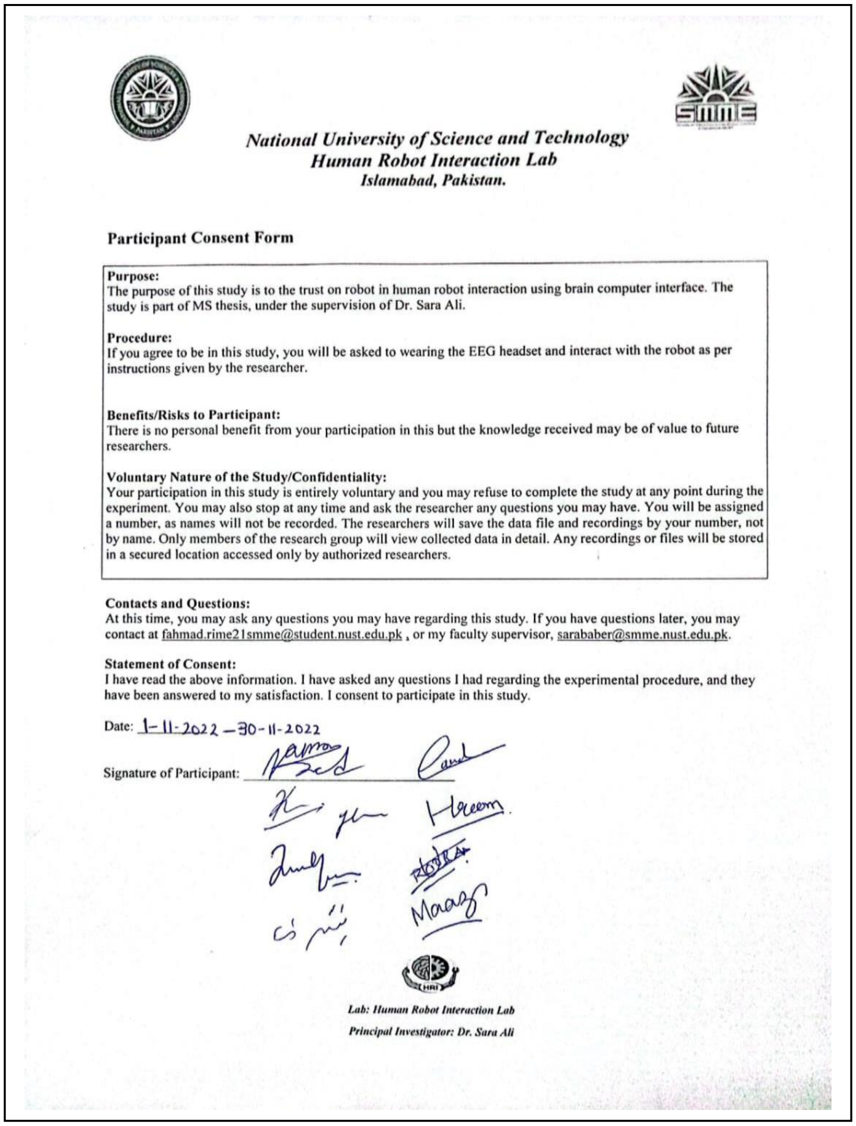
   Yes No

Date: 30/3/23

Signature of Participant:

Lab: Human Robot Interaction Lab
Principal Investigator: Dr. Sara Ali

Figure 4.4: Scanned copy of the Questionnaire 2 form filled by the participants



National University of Science and Technology
Human Robot Interaction Lab
Islamabad, Pakistan.

Participant Consent Form

Purpose:
The purpose of this study is to the trust on robot in human robot interaction using brain computer interface. The study is part of MS thesis, under the supervision of Dr. Sara Ali.

Procedure:
If you agree to be in this study, you will be asked to wearing the EEG headset and interact with the robot as per instructions given by the researcher.

Benefits/Risks to Participant:
There is no personal benefit from your participation in this but the knowledge received may be of value to future researchers.

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 and recordings by your number, not by name. Only members of the research group will view collected data in detail. Any recordings or 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 fahmad.rime21smme@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.

Date: 1-11-2022 – 30-11-2022

Signature of Participant: ______________________

Lab: Human Robot Interaction Lab

Principal Investigator: Dr. Sara Ali

Figure 4.5: Scanned copy of the informed consent form signed by the participants

CHAPTER 5: RESULTS

5.1. Results from BCI

Human mental state in the intimate and personal zone is analyzed by capturing the EEG signals and then converting them into emotions. Real-time mental state data is recorded and stored during the HRI tasks.

Table 5-1: Participant's mental state values in their Personal zone before the VR experience

No. of Participants	Familiarity with robot	Stress (%)	Relaxation (%)
1	Familiar	33	26
		32	23
2	Familiar	30	24
		29	25
3	Familiar	30	24
		26	23
4	Familiar	24	23
		26	32
5	Familiar	26	27
		30	34
6	Non-familiar	27	33
		26	30
7	Non-familiar	32	17
		24	15
8	Non-familiar	30	28
		26	22
9	Non-familiar	34	23
		28	29

Table 5-2: Participant's mental state values in the intimate zone before the VR experience

No. of Participants	Familiarity with robot	Stress (%)	Relaxation (%)
1	Familiar	27	28
		28	27
2	Familiar	36	29
		30	28
3	Familiar	32	33
		30	32
4	Familiar	38	27
		26	14
5	Familiar	24	18
		32	29
6	Non-familiar	33	20
		39	28
7	Non-familiar	41	25
		26	25
8	Non-familiar	26	14
		41	36
9	Non-familiar	32	23
		34	23

Table 5-3: Participant's mental state values in Personal zone during the VR experience

No. of Participants	Familiarity with robot	Stress (%)	Relaxation (%)
1	Familiar	33	26
		32	23
2	Familiar	30	24

		22	25
3	Familiar	30	24
		26	32
4	Familiar	24	23
		26	36
5	Familiar	22	27
		30	34
6	Non-familiar	27	33
		26	30
7	Non-familiar	32	25
		24	27
8	Non-familiar	30	28
		26	22
9	Non-familiar	32	23
		23	29

Table 5-4: Participant's mental state values in the intimate zone during the VR experience

No. of Participants	**Familiarity with robot**	**Stress (%)**	**Relaxation (%)**
1	Familiar	27	28
		28	27
2	Familiar	31	29
		30	28
3	Familiar	32	33
		30	32
4	Familiar	25	27
		26	23
5	Familiar	24	22
		32	29

6	Non-familiar	33	20
		34	28
7	Non-familiar	38	25
		26	25
8	Non-familiar	26	21
		36	32
9	Non-familiar	32	23
		34	26

Table 5-5: Participant's mental state values in Personal zone after VR experience

No. of Participants	Familiarity with robot	Stress (%)	Relaxation (%)
1	Familiar	33	26
		32	23
2	Familiar	27	32
		22	25
3	Familiar	30	24
		21	32
4	Familiar	24	23
		26	33
5	Familiar	22	27
		26	34
6	Non-familiar	27	33
		26	30
7	Non-familiar	32	25
		22	35
8	Non-familiar	30	28
		26	31
9	Non-familiar	27	23

		23	29

Table 5-6: Participant's mental state values in the intimate zone after the VR experience

No. of Participants	Familiarity with robot	Stress (%)	Relaxation (%)
1	Familiar		28
		24	27
2	Familiar	26	29
		30	28
3	Familiar	32	38
		23	32
4	Familiar	25	27
		26	34
5	Familiar	24	22
		32	29
6	Non-familiar	33	20
		34	28
7	Non-familiar	34	32
		26	25
8	Non-familiar	26	26
		32	32
9	Non-familiar	32	23
		34	26

5.2. Offline processing of EEG data

Offline processing of the raw EEG data collected during the experiments is done to additionally support the results derived from the software. Two datasets were obtained during the human-robot interaction. The first dataset, namely, Dataset A was obtained during task 1 when the robot enters the personal zone of the participants. The second dataset namely, Dataset B was obtained during task 2 in which the robot enters the intimate zone of the participants. Both datasets were analyzed to compare the results of EEG data in personal and intimate zone. All the processing steps were performed in a MATLAB open-source toolbox EEGLAB. Both datasets were imported and then the insight 2.0 electrode location was assigned to all the channels. Emotive Insight headset gives the filtered data as the most popular choice of filters required to eliminate the noise and artifacts were basic FIR filter and the 50-60 Hz notch filters are built-in in the headset [18,39,40] so, there is no need to filter the data.

5.2.1. Power Spectral Density

To estimate the frequency bands PSD using Welch's method is used with a window length of 256 ms and the length of Fourier transform = 128 (Welch, 1967). EED topographical mapping shows the spatial distribution of voltage activity over the brain and in return, Spectro plots show the density of each band over the scalp. The color chart represents the power density in db, red color represents the high density while blue represents the low density. In Figure 5.1 Hz frequency represents the alpha activity and 25 Hz represents the beta activity. Figure 5.1 (a), (b) shows the Spectro-topo plots of Dataset A in which the robot enters the personal zone of the participants. From plot (a) it can be seen that 10 Hz frequency is more dominant in it as compared to plot (c) on the other hand 25 Hz frequency plot (d) shows that that the beta activity is more dominant in Dataset B as compared to the plot (b) in Dataset A. the dominance of beta activity in Dataset B concludes that the participants felt uncomfortable or alert when the robot enters the intimate zone of the participants while the dominance of alpha activity in Dataset B shows that the participants are more relaxed when the robot enters the personal zone as compared to when it enters the intimate zone of the participants.

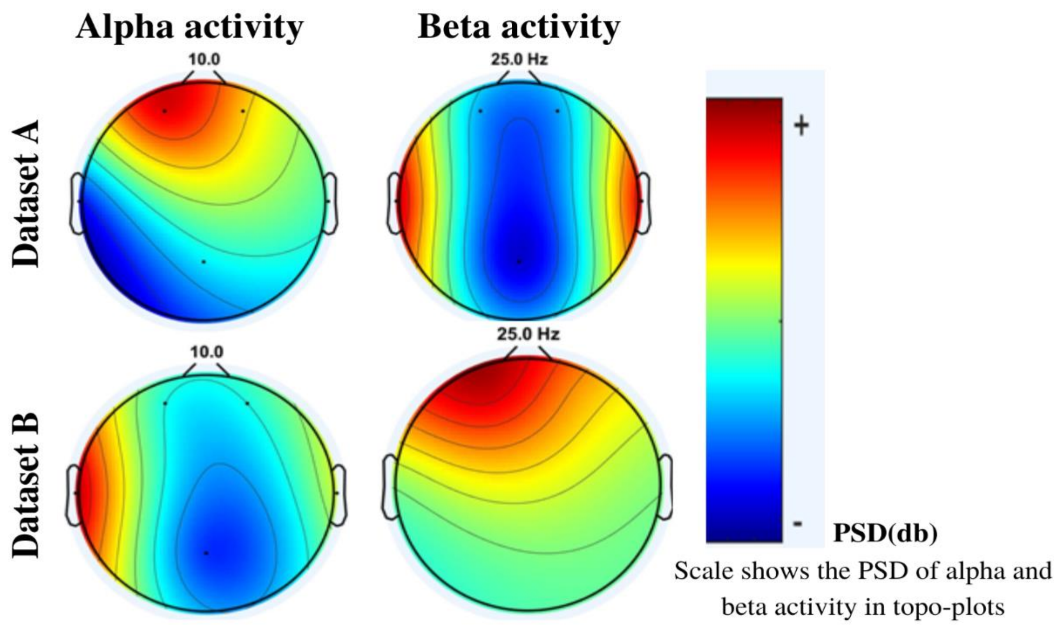


Figure 5.1: (a), (b) Spectro-topo plot representation of EEG Dataset A and (c), (d) represents topo plots of Dataset B. Mental state is visualized based on PSD value. The figure shows that alpha activity is dominant in dataset A as compared to dataset B.

5.3. Statistical Analysis

5.3.1. Descriptive Statistical Analysis

Table 5-7 shows the mean and std. deviation values of stress and relaxation in both tasks. Participants felt more comfortable in the personal zone compared to the intimate zone as the mean value of the stress is 32.1% in the intimate zone with the std. Deviation of 4.99 and the value of stress in the personal zone is 26.6% with the std. Deviation of 6.16. As the stress value is increased in the intimate zone, the relaxation value is decreased as the participants felt uncomfortable. The mean value of relaxation in the intimate zone is 25.1% with the std. Deviation of 3.52 and 27.7% in the personal zone with the std. Deviation of 5.92.

Table 5-7: Stress and Relaxation values for familiar and non-familiar participants in both zones

		Personal zone		Intimate zone	
		Stress	**Relaxation**	**Stress**	**Relaxation**
Familiar participants	Mean	28.6	26.1	30.3	26.5
	Std. Deviation	2.95	4.26	4.37	5.94
Non-Familiar participants	Mean	29.4	25.7	33.7	25.5
	Std. Deviation	3.95	7.50	5.62	7.51

Table 5-8 shows the descriptive analysis of the results of BCI obtained before the VR task, during the VR task, and after the VR task. Participants felt more comfortable interacting with virtual robots as compared to interacting with real robots as the mean value of stress in the intimate zone of the real world is 32% which is greater than the mean value of stress in the intimate zone of virtual reality which is 30.2%. VR experience improves the trust in robot and human-robot interaction in the real world as the mean value of stress after VR experience is 29% which is less than the stress in real-world interaction before the VR experience.

Table 5-8: Participant’s mental state values in both zones

		Personal zone		Intimate zone	
		Stress	**Relaxation**	**Stress**	**Relaxation**
Before VR Experience	Mean	28.5	26.4	32	25.5
	Std. Deviation	3.05	3.81	5.36	6.04
During VR Experience	Mean	27.5	28.2	30.2	26.5
	Std. Deviation	3.68	4.25	4.02	3.79
After VR Experience	Mean	26.4	28.5	29	28
	Std. Deviation	3.74	4.13	3.98	4.40

5.3.2. Inferential Statistical Analysis

The acquired data in the form of human mental state (stress and relaxation) during the experiment for both tasks have been validated using the statistical tool two-way ANOVA. The First row in Table 5-9 shows the results of the two-way ANOVA for the H1 hypothesis that there is a difference in the mental state of the participant in the personal zone and intimate zone. This hypothesis is proved by the results as the value of $p < 0.05$ and the F-value is greater than the F-critic value. The second and the third row in Table 5-9 shows the results of two-way ANOVA for the H2 hypothesis, it also shows that there is a significant difference in the mental state of the participants who are familiar with the robot and the non-familiar participants in the intimate and personal zone, as the value of $p < 0.05$ and F-value is greater than the F-critic value.

Table 5-9: Statistical Analysis of the BCI Results

ANOVA of	F	P-value	F-crit
All participants in both zones	8.3356	0.00506	3.9668
Familiar and No-familiar in the intimate zone	12.9644	0.00094	4.1132
Familiar and No-familiar in the personal zone	4.8853	0.03352	4.1132

5.4. Results from Questionnaire

Survey-based analysis of participants is carried out for the comparison of BCI results with the questionnaire results. There are five questions Q1 is related to the safe interaction with the robot, Q2 is about the trust in a robot, Q3 is related to the perception of participant related to the movement of the robot, Q4, and Q5 is about the human perception about the comfort zone that in which zone human feels comfortable.

In Table 5-10 Questionnairen1, results show that 85% of participants felt safe and trusted the robot while interacting with it. The perception of the participants related to the movement of the robot is that they felt comfortable with the way the robot moves as the Nao robot walks just like humans. All the participants felt comfortable in the personal zone but 40% of participants felt uncomfortable as the robot enters their intimate zone. However, 75% of familiar participants felt comfortable with the robot in their intimate zone as they have prior experience and interaction with that robot.

Table 5-10: Results from Questionnaire 2 filled by the participants

Participants No.	**Familiarity with robot**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
1	Familiar	Yes	Yes	No	No	No
2	Familiar	Yes	Yes	No	No	No
3	Familiar	Yes	Yes	No	No	No
4	Familiar	Yes	Yes	No	No	Yes
5	Non-familiar	Yes	Yes	No	No	No
6	Non-familiar	No	No	Yes	No	Yes
7	Non-familiar	Yes	Yes	Yes	No	Yes
8	Non-familiar	Yes	Yes	No	No	No
9	Non-familiar	Yes	Yes	No	No	Yes

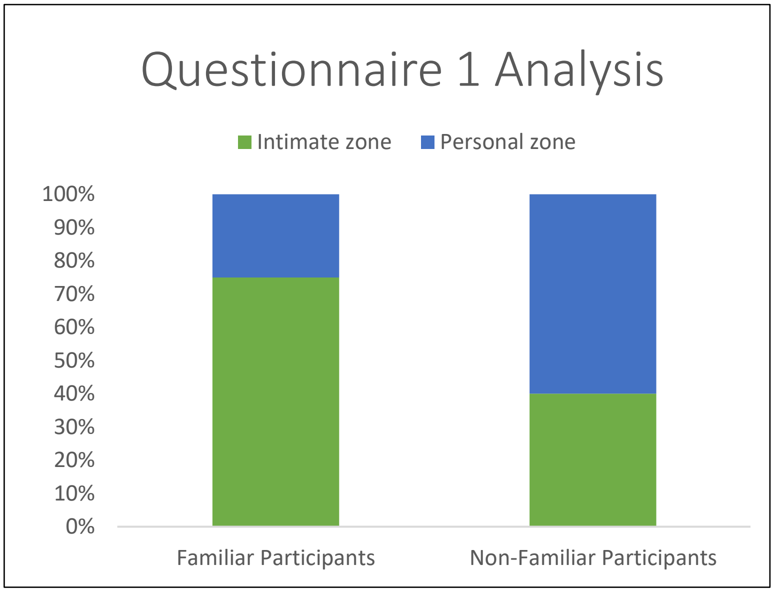


Figure 5.2: Results of the Questionnaire 1 form filled by the participants

Questionnaire 2 was used for the survey-based analysis of the participants for the comparison of BCI results with questionnaire results. This analysis was carried out to know how human-robot proxemics affects the participant's comfort and trust in the robot. Q1 is related to the comparison of safe interaction in VR and the real world, and Q2 and Q3 are about the participant's comfort in HRI zones of VR and the real world. Q5 is about the pre-training in VR improving the trust in robots during real-world human-robot interaction.

In Table 5-11 Questionnaire 2 results show that 85% of participants felt safe while interacting with the robot in VR as compared to real robots as they considered real robots less controllable. The results indicate that there are significant differences in how humans react to robots in virtual environments compared to real-world settings. As 85% of participants felt comfortable when the robot enters the personal and intimate HRI zones of the participants in VR as compared to when the robot reached the participants in the real world. 75% of participants agreed to this that pre-training in human-robot interaction in VR improves trust in robots in the real world.

Table 5-11: Results from Questionnaire 2 filled by the participants

Participants No.	Familiarity with robot	Q1	Q2	Q3	Q4
1	Familiar	Yes	Yes	Yes	Yes
2	Familiar	Yes	Yes	Yes	Yes
3	Familiar	Yes	Yes	Yes	Yes
4	Familiar	Yes	Yes	Yes	Yes
5	Non-familiar	Yes	Yes	Yes	Yes
6	Non-familiar	No	No	No	No
7	Non-familiar	Yes	Yes	Yes	No
8	Non-familiar	Yes	Yes	Yes	Yes
9	Non-familiar	Yes	Yes	Yes	Yes

CHAPTER 6: CONCLUSION

This study compared the quantitative proxemics to measure the trust in robots during HRI. The BCI results from our study indicated that people preferred to interact with the robot in their personal zone as compared to in their intimate zone confirming our first hypothesis (H1). Familiarity with the robot also influences the proximity as people familiar with the robot felt comfortable and trust in the robot more than the people who are not familiar with the robot and never interact with it (confirming H2). Results from the statistical analysis also support H1 and H2. From the BCI results and the survey-based analysis, we also found that people perceived the real robot to be less controllable than the virtual robot confirming the H3 hypothesis that people trust virtual robots more than real robots. Additionally, the BCI results show that people are more stressed and the level of relaxation is less before conducting the VR interaction, and after VR interaction, they are less stressed and more comfortable so we conclude that according to our hypothesis (H4), VR training improves the trust in robot and helps to make people comfortable with a real robot. Overall, the study provides valuable insights into the factors that influence people's trust in robots during HRI, such as proximity and familiarity, and suggests that VR training can effectively improve trust in robots. These findings could have practical implications for the design and implementation of robots in various settings, such as healthcare, education, and entertainment.

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